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Recovery from Security Intrusions in Cloud Computing

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À minha família que esteve sempre presente e sempre me apoiou em todos os momentos e decisões

Abstract

The number of applications being deployed using the *Platform as a Service* (PaaS) cloud computing model is increasing. Despite the security controls implemented by cloud service providers, we expect intrusions to harm these applications. We present Shuttle, a novel intrusion recovery service where security intrusions in PaaS applications are removed and tolerated. PaaS providers are capable to allow their customers to recover from intrusions in their applications using Shuttle.

Our approach allows undoing changes to the state of PaaS applications due to intrusions, without loosing the effect of legitimate operations performed after the intrusions took place. We combine a record-and-replay approach with the elasticity provided by cloud offerings to recover applications deployed on various instances and backed by distributed databases. To recover applications from intrusions, the service loads a database snapshot taken before the intrusion and replays the subsequent requests, in concurrently as possible, while continuing to execute incoming requests. Shuttle is available without setup and configuration to the PaaS application developers. The proposed service removes security intrusions due to software flaws or corrupted user requests and supports corrective and preventive maintenance of applications deployed in PaaS cloud computing platform.

We present an experimental evaluation of Shuttle on Amazon Web Services (AWS). We show Shuttle can replay 1 million requests in around 10 minutes and that it is possible to duplicate the number of requests replayed per second by increasing the number of application servers from 1 to 3.

Keywords

- Intrusion Recovery
- Intrusion Tolerance
- Dependability
- Cloud Computing
- Platform as a Service
- Distributed Database Systems

Resumo

O número de aplicações instaladas usando o modelo Plataforma como Serviço (PaaS) tem aumentado. Apesar dos mecanismos de controlo de segurança implementados pelos operadores de serviços de computação em nuvem é expectável que estas aplicações sejam afectadas por intrusões. Neste documento introduzimos um novo serviço de recuperação de intrusões designado por Shuttle. O Shuttle permite que os operadores ofereçam um serviço através do qual os seus clientes podem recuperar de intrusões às suas aplicações.

A nossa abordagem permite inverter as alterações ao estado da aplicação provocadas por intrusões, sem comprometer o efeito de operações legítimas que ocorram após a intrusão. A abordagem de gravar e re-executar é combinada com a elasticidade oferecida pelo modelo de computação em nuvem para recuperar de intrusões a aplicações instaladas em várias instâncias e suportadas por uma base de dados distribuída. Para realizar a recuperação, o serviço carrega uma cópia da base de dados, gravada antes da intrusão ocorrer, e repete os pedidos posteriores, tão em paralelo quanto possível, enquanto processa novos pedidos.

A avaliação experimental realizada no serviços de computação na nuvem da Amazon (AWS) demonstra que o Shuttle é capaz de repetir 1 milhões de pedidos em aproximadamente 10 minutos e que é possível duplicar o número de pedidos repetidos por segundo aumentando o número de servidores de 1 para 3.

Palavras Chave

- Recuperação de Intrusões
- Tolerância de Intrusões
- Dependência
- Computação em Nuvem
- Platforma como Serviço
- Sistemas de Bases de Dados Distribuídas

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Abbreviations

ACID *Atomicity, Consistency, Isolation and Durability*

API *Application Programming Interface*

AWS *Amazon Web Services*

BDB *Berkeley DB*

CAP *Consistency, Availability, Partition Tolerance*

CPU *Central Processing Unit*

CRUD *create, read, update and delete*

CSP *Cloud service provider*

DBMS *Database Management System*

DHT *Distributed Hashtable*

DOM *Document Object Model*

EBS *Elastic Block Store*

EC2 *Elastic Compute Cloud*

ECU *EC2 Compute Unit*

HTTPS *Hypertext Transfer Protocol Secure*

HTTP *Hypertext Transfer Protocol*

IaaS *Infrastructure as a Service*

IDL *Interface Description Language*

IDS *Intrusion detection system*

IMAP *Internet Message Access Protocol*

IOPS *Input/Output Operations Per Second*

IP *Internet Protocol*

ITIL *Information Technology Infrastructure Library*

JAX-WS *Java API for XML Web Services*

JIT *Just-in-time*

JVM *Java Virtual Machine*

MVC *Model View Controller*

NIO *Non Blocking IO*

NIST *National Institute of Standards and Technology*

NoSQL *Not only SQL*

OWASP *Open Web Application Security Project*

PaaS *Platform as a Service*

protobuf *Google Protocol Buffers*

Q&A *Questions and Answers*

REST *Representational State Transfer*

RID *Request ID*

RMI *Remote Method Invocation*

RPC *Remote Procedure Call*

S3 *Simple Storage Service*

SaaS *Software as a Service*

SID *Snapshot ID*

SOAP *Simple Object Access Protocol*

SQL *Structured Query Language*

SRD *Shuttle Request Data*

SSD *Solid State Disk*

SSH *Secure Shell*

SSL *Secure Socket Layer*

TCP *Transmission Control Protocol*

TID *Thread Id*

VM *Virtual Machine*

VPC *Virtual Private Cloud*

YCSB *Yahoo! Cloud Serving Benchmark*

1

Introduction

Platform as a Service (PaaS) is a cloud computing model that supports automated configuration and deployment of applications [1–4]. While the *Infrastructure as a Service* (IaaS) model is being much used to obtain computation resources and services on demand [3, 5], PaaS aims to reduce the cost of software deployment and maintenance abstracting the underlying infrastructure. The model defines a well tested and integrated environment in which clients (*tenants*) design, implement, deploy and run their applications on a managed cloud infrastructure through a set of middleware services. Examples of these services are load-balancing, automatic server configuration and storage. These services are paid-per-usage and turn the application easy to deploy and scale. PaaS platforms are provided either by cloud providers, such as Windows Azure [6], Google App Engine [7], Heroku [8], Openshift [9] and Amazon Elastic Beanstalk [10], or by open source projects [11–13]. Besides natural metrics such as cost and performance, the success of PaaS systems will also be established by their features, for instance capability to recover from intrusions.

1.1 Problem Statement

The number of applications running in cloud computing platforms, including those based on the PaaS model, is increasing rapidly. Many of these applications are critical for their companies and contain valuable information, so the exploitation of vulnerabilities is attractive and profitable. Consequently, the risk of intrusion is high. An intrusion happens when an attacker exploits a vulnerability successfully. Intrusions are considered faults. Faults may cause system failure and, consequently, application downtime and significant business losses [14]. The recent case of the cloud-based Code Spaces service is conspicuous: hackers deleted most of its data and backups, leading to the termination of the service [15].

Cloud service provider (CSP) implement several security controls. Most of these controls aim to prevent and detect intrusions: access control, firewalls, intrusion detection and prevention systems, network access control, vulnerability scanning, etc. Despite the importance of these mechanisms, applications often contain design or configuration vulnerabilities that let intrusions happen [16, 17]. Complexity and budget/time constraints [18], weak users passwords or bad security policies are known causes of these problems. The recent case of the bash bug (or Shellshock) shows that there are other reasons such as legacy software being used in ways that were unpredictable when it was developed [19]. Attackers can spend years developing new ingenious and unanticipated attack methods having access to what protects the application. On the opposite side, guardians have to predict new methods to mitigate vulnerabilities and to solve attacks in few minutes to prevent intrusions.

Much research has been done on mechanisms to tolerate Byzantine faults, including intrusions [20–22]. However, most of these techniques do not prevent application level attacks or user mistakes. For instance, if attackers steal legitimate user credentials, they are able to modify the state of the applications violating their security policy. In summary, there are several paths for intrusions to happen, even if mechanisms to prevent or tolerate them are used.

We assume intrusions can happen and their effects need to be removed from the applications' state. This removal is often done manually by system administrators. Administrators have to detect the intrusion, understand the parts of the state compromised directly by the intrusion or contaminated by operations that used compromised state, and clean the state manually. For instance, most of full-backup solutions revert the intrusion effects but require extensive system administrator effort to restore the effect of the legitimate actions. This process is error-prone, often takes long and causes application downtime [23]. Intrusion recovery systems aim to automate these steps and mitigate these issues.

Previous intrusion recovery systems targeted operating systems [24, 25], databases [26, 27], web applications [28–30] and other services [31]. Yet, none of them was designed for cloud applications, which are often deployed in multiple servers and use background databases. Furthermore, most cause downtime, which is undesirable in online services.

1.2 Goals and Main Contributions

The primary goal of this thesis is to design, develop and evaluate a system to recover from intrusions in cloud computing. In particular, the system shall allow tenants to keep their PaaS applications operational despite intrusions. The idea is to accept intrusions can happen, thus to provide a system to remove their effects from the application's state and restore the state's integrity.

The approach followed in this dissertation consists in recovering the applications state when intrusions happen, instead of trying to prevent them from happening. Intrusion recovery systems do not aim to substitute prevention but to be an additional security mechanism. Similarly to fault tolerance, we accept that faults occur and have to be processed. However, we aim to decrease the applications'

Mean Time to Repair (MTTR), not the Mean Time to Failure (MTTF). Doing so, we expect to increase the applications' availability, which is given by $Availability = MTTF/(MTTF + MTTR)$.

The main contribution of this dissertation is a novel *intrusion recovery service* for PaaS systems, named *Shuttle*. Shuttle is a service that aims to make PaaS applications operational despite intrusions, helping tenants to recover their applications from software flaws and malicious, or accidental, corrupted user requests without requiring application downtime during the process. When an intrusion is detected, tenants can use this service, which is offered by the CSP, to remove intrusions' effects and recover the integrity of their applications. In this dissertation, we are concerned with the applications' availability and the integrity of their state, not their confidentiality. Consequently, the proposed service does not aim to deal with information leaks.

Shuttle assumes a client-server model in which clients communicate with the servers in the cloud using *Hypertext Transfer Protocol* (HTTP)/*Hypertext Transfer Protocol Secure* (HTTPS) or protocols encapsulated on top of them (e.g., SOAP, REST). For each application deployed in the PaaS system, Shuttle records the requests issued by clients and creates periodic snapshots of the application database.

After detection of the intrusion, Shuttle loads the snapshot that precedes the beginning of the intrusion and replays only the legitimate requests to recreate an intrusion-free application state. Requests are replayed asynchronously and, whenever possible, concurrently. Even so, the recovery process is deterministic because operations to each data item must have the same order as on first execution.

Dependencies established at database level during the requests' first execution are used to create independent clusters of requests that can be replayed concurrently. We propose a branching mechanism to maintain the service available continuing to execute incoming requests while replaying the requests.

We introduce a novel approach to remove the intrusion effects in which the PaaS controller terminates the current application instances, launches new instances and deploys an updated software version, which may fix previous flaws.

Unlike previous intrusion recovery systems, Shuttle is provided as a service to developers and tenants of PaaS applications. Consequently, it can be well tested and available without depending on being correctly setup by the application developers. We also leverage the elasticity of PaaS infrastructures to reduce the service costs and the recovery period. Specifically, Shuttle is designed to allocate more servers during the recovery period to accommodate the throughput of requests being replayed, and release them at the end, with a proportional impact on service costs. The decline in computation and storage costs in public cloud providers makes affordable to store user requests, to use database snapshots and to replay previous user requests.

We propose, to the best of our knowledge, the first intrusion recovery service for PaaS applications. The main contributions of this dissertation are the following:

- a new intrusion recovery approach provided as a service integrated in a PaaS system and taking into consideration applications running in various instances backed by distributed databases;

- a method to order the replayed user requests considering their accesses to databases;
- accomplishing intrusion recovery without service downtime using a branching mechanism;
- leveraging the resource elasticity and pay-per-use model in PaaS environments to record and launch multiple clients to replay previous non-malicious user requests as concurrently as possible to reduce the recovery time and costs;
- a mechanism to do a globally transaction-consistent snapshot of NoSQL databases;
- an approach to remove intrusions redeploying the applications;

1.3 Thesis Structure

This document is structured as follows. In Chapter 2, we present the fundamental concepts and previous intrusion recovery proposals. In Chapter 3, we describe the architecture of PaaS systems and the proposed mechanism for intrusion recovery service. In Chapter 4, we describe the platform and components of the prototype of Shuttle. The work is evaluated in Chapter 5 and concluded in Chapter 6.

2

Context and Related Work

In this chapter, we give background information on relevant concepts and techniques that are relevant in this thesis. We start by introducing the main concepts of dependability in Section 2.1. This includes a discussion of intrusions and methods to avoid or tolerate them. Section 2.2 introduces the main intrusion recovery techniques. Each of the following sections describe a number of relevant proposals for recovery in the levels where PaaS applications are attacked: operating system, database and application. Finally, Section 2.3 discusses the contributions of these works in the context of this dissertation.

2.1 Dependability Concepts

The *dependability* of a computing system is the ability to deliver a trustworthy service [32]. In particular, the concept of dependability encompasses the following attributes:

- Availability: service readiness for authorized users;
- Confidentiality: absence of unauthorized disclosure of information;
- Safety: absence of catastrophic failures;
- Reliability: continuity of correct service;
- Integrity: absence of improper system state.

Three core concepts in dependability are: fault, error and failure.
A *fault* is the cause of an error. The source of a fault belongs to the software or hardware domain and it can be introduced either *accidentally* or *maliciously* during the system development, production or operation phases [32, 33]. Faults can deviate the system from its specified behavior leading

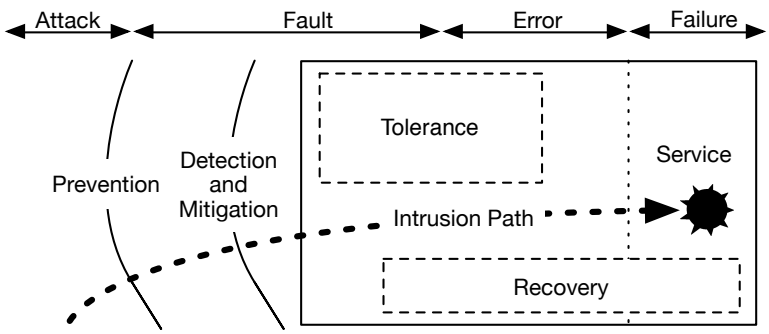


Figure 2.1: Intrusion path across the system

to errors (Figure 2.1). *Errors* are the part of the system state that may cause a subsequent failure. A system *failure* occurs when errors become observable at the system interface. In the context of this work, we consider faults which are generated by humans in an accidentally or deliberate, malicious or non-malicious way. In particular, we target software flaws faults and interaction faults from input mistakes, attacks and intrusions [32].

An *intrusion* is a malicious fault resulting from an intentional vulnerability exploitation. As originally proposed generically for faults [32, 34], intrusions can be omissive, suspending a system component, and/or assertive, changing a component to deliver a service with a not specified format or meaning. In order to develop a dependable system, delivering a resilient service, we can use a combination of intrusion forecast, prevention, detection, mitigation, tolerance and recovery (Figure 2.1).

Intrusion forecast and prevention are realized by design and they seek to prevent future attackers from exploiting vulnerabilities. However, preventing intrusions by design is hard. Software has flaws due to its complexity and budget/time constraints [18, 33]. System administrators, as humans, can make security configuration mistakes or users may grant access to attackers [23]. Moreover attackers can spend years developing new ingenious and unanticipated intrusions having access to what protects the system while the guardians have to predict them. Due to this asymmetry, it is arguably impossible to protect all vulnerabilities by design. Therefore the vulnerabilities of prevention mechanisms can be exploited successfully leading to an intrusion. A vast number of vulnerabilities and attacks are listed for instance in the National Vulnerability Database [35].

Intrusion detection and mitigation mechanisms monitor the system to detect suspicious actions that may be connected with an intrusion. However, *Intrusion detection system* (IDS) turn the system attack-aware but not attack-resilient, that is, they cannot maintain the integrity and availability of the system in face of attacks [36]. IDS may not detect unknown vulnerabilities. Moreover, attackers may use encrypted actions or use legitimate requests.

Intrusion tolerance is the last line of defense against attacks before the system failure occurs (Figure 2.1). Intrusion tolerance is the ability of a system to keep providing a, possibly degraded but adequate, service during and after an intrusion [37]. Instead of trying to prevent every single intrusion, these are allowed, but tolerated. The system has mechanisms to prevent the intrusion from generating a system failure [21]. Intrusion tolerance mechanisms hide the errors effects using redundancy mechanisms or using intrusion recovery systems, which detect, process and recover from intrusions.

Many intrusion tolerance mechanisms are based on replicating state with Byzantine fault-tolerant protocols [20, 38, 39]. The idea is to ensure that a service remains operational and correct as long as no more than a certain number of replicas are compromised. Replicas can be implemented in different manners to provide diversity, to reduce the risk of common failure modes. In addition, a proactive recovery mechanism can reboot the replicas periodically to rejuvenate and restore their soft-state and security assets, e.g., keys [20, 40, 41]. In *disaster recovery* solutions, the state is replicated in remote sites, allowing the recovery from catastrophes that destroy a site [42].

The above-mentioned replication mechanisms for intrusion tolerance can tolerate some intrusions targeted at design faults (vulnerabilities), as long as diversity is used. However, most of the fault tolerance mechanisms do not prevent accidentally or malicious faults at application level, e.g., using valid user requests. Most of state replication mechanisms facilitate the damage to spread from one site to many sites as they copy data without distinguishing between legitimate and malicious sources. Furthermore, most of proactive recovery techniques rejuvenate only the application soft-state but intrusions can affect its persistent state. Consequently, intrusions may transverse these intrusion tolerance mechanisms and cause a system failure.

2.2 Intrusion Recovery

The main focuses of this thesis are intrusion recovery mechanisms that accept intrusions happen but detect, process and recover from their effects. These mechanisms remove all actions related to the intrusion, their effects on legitimate actions and return the application to a correct state. These mechanisms can be used to tolerate intrusions or to recover from system failures. In order to recover from intrusions and restore a consistent application behavior, the system administrator detects the intrusion, manages the exploited vulnerabilities and removes the intrusion effects. This process should change the application state to an intrusion-free state.

The first phase of intrusion recovery, out of the scope of this work, concerns the intrusion detection. Automated IDS are used to detect intrusions or suspicious behaviors. This phase may need human intervention to prevent false positives, which trigger recovery mechanisms and can result in legitimate data losses. Thus the detection phase can be a significant delay. The detection delay should be minimized because intrusion effects spread in the meantime between intrusion achievement and

detection. Moreover, intrusion recovery services should provide tools to help system administrators to review the application behavior and determine which weaknesses were exploited.

The second phase, also out of the scope of this work, is vulnerability management. Vulnerabilities are identified, classified and mitigated after their detection by a group of persons which the *National Institute of Standards and Technology* (NIST) names as the patch and vulnerability group [43]. Vulnerabilities are fixed by configuration adjustments or applying a security software patch, i.e., by inserting a piece of code developed to address a specific problem in an existing piece of software.

The third phase, and the one that this work is about, consists in removing the intrusion effects. Intrusions affect the application integrity, confidentiality and/or availability. To recover from availability or confidentiality violations is out of the scope of this document. However, we argue that the design of the applications should encompass cryptography techniques which may reduce data relevance and protect the data secrecy [44].

Intrusion removal processes recover from integrity violations recreating an intrusion-free state. Due to the fact that the system availability is result of the integrity of each system component [45], these processes contribute to recover the system availability. Moreover, the removal processes should not reduce the system availability. We argue that intrusion recovery services should avoid the system downtime and support the execution of recovery processes in background without externalization to users. Intrusion recovery mechanisms can accomplish some of the goals of intrusion tolerance if they keep providing a, possibly degraded but adequate, service during and after an intrusion recovery.

The following sections explain distinct recover processes where the application integrity is restored by determining the effects of the detected intrusion actions, reverting them and recreating a correct state.

2.2.1 Formalization of the Recovery Process

As discussed in previous section, intrusion recovery services detect the intrusion effects, revert them and restore the application to a correct state. Here we explain this process by formally modeling the application as a sequence of actions and outline the distinct approaches to perform intrusion recovery.

An application execution is modeled as a set of actions A and a set of objects O. Actions are described by a type (read, write, others more complex), the value(s) read/written, and a timestamp (which defines the order of the actions). Each object has a state or value and a set of operations that can modify it. We specify $A_{intrusion}$ as the subsequence of actions of A whereby the attacker compromises the application during the intrusion, A_{after} as the subsequence of actions that begins after the intrusion begin (including the first action of the intrusion) and A_{legal} as the subsequence of legitimate actions in A. Notice that $A_{legal} = A - A_{intrusion}$.

A recovery service aims to set the state of a service to $O_{recovered}$ at the end of the recovery pro-

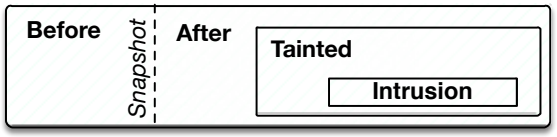


Figure 2.2: Set of actions of an application execution

cess. The set $O_{recovered}$ shall be composed of objects as if their state was defined exclusively by a set of legitimate actions $A_{recovered}$. Objects of the subset $O_{recovered}$ represent a new *intrusion-free* and *consistent state*. A state is consistent if it is valid according to the application specification. A state is intrusion-free if it is created only by legitimate actions. If the application respects the specification (correctness), then changing from O to $O_{recovered}$ performs service restoration [32], i.e., restores the application service to a correct behavior.

A basic recovery service, like a full-backup mechanism, tries to obtain, after the recovery, the subset of object values $O_{recovered}$ written before the intrusion, which do not include the attacker actions, i.e., $O_{recovered} = D - D_{after} : D_{recovered} \cap D_{intrusion} = \emptyset$.

We define the set of *tainted* actions, $A_{tainted}$, and the set of tainted objects, $O_{tainted}$, at a certain instant in the following way: if an action belongs to $A_{intrusion}$, then it belows to $A_{tainted}$; if an object belongs to $O_{intrusion}$ then it belongs to $O_{tainted}$; if an action in A_{legal} reads an object in $O_{tainted}$, then that action belongs to $A_{tainted}$; if an action in $A_{tainted}$ writes an object value in O_{legal}, then that object belongs to $O_{tainted}$ (Figure 2.2). Therefore, $A_{tainted}$ includes $A_{intrusion}$ but typically also actions from A_{legal} that were corrupted by corrupted state. Also, $O_{tainted}$ includes $O_{intrusion}$ but typically also objects from O_{legal} that were corrupted by corrupted state. Then, the set of object values written only by non-malicious actions is not the same as the set of objects obtained after removing the objects written by malicious or tainted actions, i.e., O_{legal} written by $A \cap A_{intrusion} = \emptyset$ is not equal to O_{legal} written by $D - D_{intrusion}$ or O_{legal} written by $D - D_{tainted}$. In other words, to remove the objects written by intrusions and tainted actions is necessary but not enough to obtain the values of the set of objects that would be produced only by legitimate actions.

Some intrusion recovery systems [24, 26, 27] attempt to obtain $O_{recovered}$ where the values of the objects of $O_{tainted}$ are removed from the current state O. To do so, the value of each object in $O_{tainted}$ is replaced by a previous value. These systems keep the objects written by legitimate actions, O_{legal}, unmodified.

Consider an hypothetical application execution at a certain point in time, after the intrusion, where A is replaced by the set $A_{recovered} = A - A_{intrusion} = A_{legal}$, i.e., where the intrusion actions $A_{intrusion}$ are not executed. We would have in this application: $A \cap A_{intrusion} = \emptyset \implies D_{intrusion} = \emptyset, A_{tainted} = \emptyset \implies D_{tainted} = \emptyset$. In other words, if the malicious actions are removed, then the state O does not have the objects written by $A_{intrusion}$. For this reason, the sequence of tainted actions $A_{tainted}$ is empty. The set of tainted actions in the real application execution, which includes $A_{intrusion}$, would read different values and have a different execution if $A_{intrusion}$ would be empty.

Therefore, if $A_{intrusion}$ and $O_{intrusion}$ are removed, then $A_{tainted}$ should be *replayed* because the actions of $A_{tainted}$ are not contaminated by malicious data during their re-execution. The replay process restores the application to a correct state $O_{recovered}$, which is intrusion-free.

The sequence of actions, A_{before}, performed before the intrusion, i.e., $A_{before} = A - A_{after}$, can be extensive. Each action takes a variable but not null time to perform. Therefore, to replay $A_{recovered}$: $A_{before} \subseteq A_{recovered}$ may takes an excessive amount of time. We define the subsets $O_{snapshot}(t)$ and $A_{snapshot}(t) : A_{snapshot} \subseteq A$ as the subsets of object values and actions executed before the begin of a snapshot operation at instant *t*. The snapshot operation copies the value of the object immediately or on the next write operation. If the attack is subsequent to t, then $A_{after} \cap A_{snapshot} = \emptyset \implies (A_{intrusion} \cup A_{tainted}) \cap A_{snapshot}(t) = \emptyset$, i.e., the snapshot is not affected by intrusion. For that reason, the service can replay only $A - A_{snapshot} - A_{intrusion}$ using the object set $O_{snapshot}$ as base.

The most recent works, which are explained in the following sections, define two distinct approaches to update the set of object O to $O_{recovered}$ because of changes in the execution of $A_{tainted}$: *rewind* and *selective replay*. The selective replay approach loads only the previous versions of the tainted objects, $O_{tainted}$, and replays only the legitimate operations, which were tainted, $A_{tainted} \notin A_{intrusion}$, to update the objects in O. The $O_{legal} \notin D_{tainted}$ remain untouched. The alternative approach, rewind [46], designates a process that loads a system wide snapshot previous to the intrusion moment and replays every action in $A - A_{snapshot} - A_{intrusion}$. However, this process can take a long time.

A *version* is a snapshot of a single object value before the instant t. They can be recorded with the sequence of actions that read or write them before the instant t. We define a *compensating* action as an action that reverts the effects of an original action, for instance writing a previous value. A compensation process can obtain a previous snapshot or version. For this propose, we define the sequence $A_{compensation}(t)$ as the compensation of $A_{posteriori}(t)$, the sequence of actions after instant t. The compensation process applies the sequence of compensating actions $A_{compensation}(t)$ on the current version of the objects, in reverse order, to obtain a previous snapshot or version.

Recovery services have two distinct phases: *record phase* and *recovery phase*. The record phase is the service usual state where the application is running and the service records the application actions. In order to perform replay, the application actions do not need to be idempotent but their re-execution must be deterministic. The record phase should record the actions input and the value of every non-deterministic behavior to turn their re-execution into a deterministic process. The recovery phase can have three phases: determine the affected actions and/or objects, remove these effects and replay the necessary actions to recover a consistent state, as already explained in Section 2.2. The recovery services that support *runtime recovery* do not require application downtime because the record and recovery phases can occur simultaneously.

Most of intrusion recovery services record the actions and track the objects accessed by each of them. Since the actions read and write objects from a shared set of object values O, we can establish dependencies between actions. Dependencies can be visualized as an *action dependency graph* or an *object dependency graph*. Nodes of an action dependency graph represent actions and the edges indicate dependencies though shared objects. The object dependency graph establishes dependencies between objects through actions. Dependency graphs are used to order the re-execution of actions [31], get the sequence of actions affected by an object value change [29], get the sequence of actions tainted by an intrusion [28] or resolve the set of objects and actions that caused the intrusion using a set of known tainted objects [47].

A *taint algorithm* aims to define the tainted objects $O_{tainted}$ from a source sequence of malicious actions $A_{intrusion}$ or objects $O_{intrusion}$ using the dependency graph. The *taint propagation via replay* [25] algorithm begins with the set of $O_{intrusion}$ determined by the base taint algorithm and expands the set $O_{tainted}$. It restores the values of $O_{intrusion} \cup D_{tainted}$ and replays only the legal actions that output $O_{intrusion} \cup D_{tainted}$ during the first execution. Then it replays the actions dependent from $O_{intrusion} \cup D_{tainted}$, updating their output objects. While the forward actions have different input, they are also replayed and their outputs are updated.

Dependencies are established during the record phase or at recovery time using object and action records. The level of abstraction influences the record technique and the dependency extraction method. The abstraction level outlines the recoverable attacks. In the next paragraphs, we explain the relevant works at abstraction levels where services deployed in PaaS are attacked: operating system, database and application.

2.2.2 Recovery at Operating System Level

In this section, we present the main intrusion recovery proposals for operating systems. First, we present the proposal that introduced the main dependencies for operating systems. Then, we present two intrusion recovery systems that use dependency rules and tainting propagation via replay, respectively. Finally, we present proposals to recover from intrusions in computing clusters, virtual machines and network file systems.

BackTracker [47]: Backtracker proposes a tainting algorithm to track intrusions. It does not perform any proactive task to remove or recover from intrusions but provides a set of rules for intrusion recovery in operating systems.

Backtracker proposes a tainting algorithm that does tainting analysis offline, after attack detection, as follows. First a graph is initialized with an initial set of compromised processes or files, $O_{tainted}$, identified by the system administrator. Then, Backtracker reads the log of system calls from the most recent entry until the intrusion moment. For each process, if it depends on a file or process currently present in the graph then the remaining objects dependent from the process are also added to the

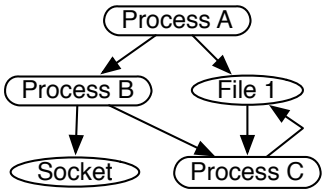


Figure 2.3: Dependency graph generated by BackTracker

graph. The result is a dependency graph (Figure 2.3) with the objects, including $O_{intrusion}$, which the compromised objects depend on. The following dependency rules establish the graph edges:

- *Dependencies process-process:*
  - *Process depends on its parent process*: Processes forked from tainted parents are tainted.
  - *Thread depends on other threads*: Clone system calls to create new threads establish bi-directional dependences since threads share the same address space. Algorithms to taint memory addresses [48] have a significant overhead. Signaling communication between processes also establish dependencies.
- *Dependencies process-file:*
  - *File depends on Process:* If the process writes the file.
  - *Process depends on File:* If the process reads the file.
- *Dependencies process-filename:*
  - *Process depends on filename:* If the process issues any system call that includes the filename, e.g., open, create, link, mkdir, rename, stat, chmod. The process is also dependent of all parent directories of file.
  - *Filename depends on process:* If any system call modifies the filename, e.g., create, link, unlink, rename.
  - *Process depends on directory:* If the process reads one directory then it depends on every all filenames on directory.

Objects shared between many processes, e.g., */tmp/* or */var/run/utmp* are likely to produce false dependencies leading to false positives. Therefore, Backtracker proposes a *white-list* filter that ignores common shared files. However, this technique relies in the system administrator knowledge. Moreover, it generates false negatives because it allows the attackers to hide their actions in objects that belong to the white-list.

Taser [24]: Taser removes the intrusion effects from the file system used by the operating system. To do that, it loads a previous version of each tainted file, $O_{tainted}$, from a file-system snapshot, $O_{snapshot}(t)$. Then, to recover the tainted objects, it replays the legitimate modification actions of each tainted object since the snapshot instant t.

Taser relies on Forensix [49] to audit the system actions during the record phase. Forensix logs the names and arguments of every system call related to process management, file system operations and networking. In order to determine the intrusion effects, Taser builds a *object dependency graph* using a set of rules similar to the rules of Backtracker [47]. The object definition encompasses files, sockets and processes. Since these rules result in a large number of false dependencies, which mark legitimate objects as *tainted*, Taser provides not only a white list mechanism but also establishes optimistic policies that ignore some dependencies. However, attackers can leverage these optimistic policies to penetrate the operating system.

The recovery phase is started with a set of tainted objects provided by an system administrator or an IDS. The provided set of objects can either be the source or the result of an attack. In the latter case, Taser, like Backtracker [47], transverses the dependency graph in reverse causality order to identify the set of attack source objects, $O_{intrusion}$, which compromised the provided objects. After, at *propagation phase*, Taser transverses the dependency graph from the source objects of the attack, $O_{intrusion}$, to the current moment, adding all tainted objects to the set $O_{tainted}$.

Taser removes the intrusion effects loading a previous version of the tainted objects from a file-system snapshot, $O_{snapshot}(t)$. Then, to recover a coherent state, Taser performs *selective replay*, i.e., it replays, sequentially, the legitimate write operations of the tainted files since the snapshot. Non-tainted files remain unchanged. Since Taser does not checkpoint the state of processes nether the input of each system call, the system must be restarted to remove the current non-persistent states and processes must be replayed from the beginning to load their non-persistent state and perform their system calls with the correct state. This issue has a significant overhead specially for long-run processes as web servers.

Taser does not update the objects originally dependent from tainted objects. In other words, the replay process only recovers a consistent state for the originally tainted objects. Therefore, Taser ignores the set of actions that read the modified version of the tainted files and have a different execution and output. This problem is addressed in [50]. Moreover, Taser uses rules to determine the affected files and remove their effects, so it can mistakenly mark legitimate operations as tainted and induce to legitimate data losses.

RETRO [25]: RETRO provides the capability of removing files affected by a set of identified attacking actions. It restores the corrupted files to a previously version using a file system snapshot and then performs selective replay using *taint propagation via replay*.

During the record phase, the kernel module of RETRO creates periodic snapshots of the file system. RETRO logs the input and the output objects of each system call and their associated process. The object definition encompasses not only files and directories but also *Transmission Control Protocol* (TCP) sessions and the operating system console (tty). Dependencies are established per system call instead of per process. Therefore, the graph is finer-grained than the graph of Backtracker [47] and reduces the number of false positives.

During the recovery phase, RETRO requires the system administrator to identify $A_{intrusion}$, pro-

cesses, system calls or $O_{intrusion}$ objects which caused the intrusion. First, it removes the malicious system calls from the graph. Then it performs *taint propagation via replay*. To do so, it loads a previous version, from a snapshot, of the objects in $O_{intrusion}$. Then, the system calls, which are dependent from the restored objects, are replayed and their output objects are updated. The forward system calls, which depend on the updated objects, are also replayed while their inputs are different from the first execution. The propagation is done thought the output of system calls with different execution. The recovery process terminates when propagation stops. Since RETRO records the system call input, it can replay processes with system call granularity instead of process granularity, so the replay process may stop earlier. However, this mechanisms forces that the process re-execution has the same sequence of system calls as its first execution. Therefore, the process source code nether its sequence of actions can not change.

Since RETRO replays the processes, the external state may change. External changes are manifested through operating system console and network objects. RETRO emails the system administrator with the textual difference between the original and recovery outputs. Later work of the same authors, *Dare* [51], extends RETRO to recover from intrusions in distributed systems. It adds the dependencies through sockets. Machines involved in a network session add socket objects to the dependency graph. Network protocol, source and destination *Internet Protocol* (IP) and ports and one ID, which are exchanged in every package during the connection, globally identify each socket object. The recovery phase in Dare is similar RETRO except on network system calls handlers. Compromised network sessions must be replayed since their input depends on destination server. Therefore, prior to invoke the system call for network session establishment, Dare invokes a remote method at receiver Dare daemon to rollback the network session. The receiver rollback the dependent objects to the version before session establishment and replays their dependencies. The remote method response includes the re-execution output. The local system updates the system call output. The re-execution is propagated if this output is different.

The efficiency of RETRO comes from avoiding to replay the actions if their input remains equal. However, the invoked system call must remain the same. Therefore, RETRO does not support a distinct process execution. RETRO requires human intervention to solve external inconsistencies. Dare solves it but it is limited to clusters where every operating system runs a Dare and RETRO daemon. RETRO can not recover from an intrusion whose log files have been garbage collected or deleted. Dare supports distributed re-execution but, as RETRO, the affected machines must be offline because its propagation algorithm shutdown the service during the repair phase.

Bezoar [48]: Bezoar proposes a rewind based approach to recover from attacks coming from the network in virtual machines (VM). The snapshot is performed by *Virtual Machine* (VM) forking using copy-on-write. This snapshot technique encompasses the entire system: processes and kernel spaces, resources, file system, virtual memory, *Central Processing Unit* (CPU) registers, virtual hard disk and memory of all virtual external devices. Bezoar tracks how the data from network connections propagates in memory. During the recovery phase, the system administrator identifies the network

connections used by the attackers. Bezoar removes the intrusion effects using rewind. It loads a previous VM snapshot and it replays the system execution ignoring all network packets from the identified malicious sources.

The recovery process using rewind is longer than RETRO or Taser because all external requests are replayed but supports distinct process execution. Bezoar requires system outage during the replay phase and does not provide any external consistency warranties.

Repairable File System (RFS) [52]: RFS is designed to recover compromised network file systems. The novelty in RFS comparing with the previously introduced systems is its client-server architecture. RFS includes a client and a server module for a network file system (NFS).

The client module tracks the system calls using ExecRecorder [53] and establishes the dependence between processes and NFS requests. Every request to the NFS server is marked with a request ID and the client ID. At server side, the request interceptor logs all requests sent by clients to update files. Requests are ordered in per-filename queues. They are processed locally and write operations are mirrored to external server asynchronously after reply. The external server keeps all file versions.

During the recovery phase, the server defines the contaminated processes using the client logs. A process is contaminated if it matches a set of rules similar to Backtracker [47]. RFS adds the concept of contaminated file and contaminated file block. If a file is contaminated, all its blocks are contaminated. The reverse is not true, i.e., processes remain non-contaminated if they read a legitimate block of a contaminated file. RFS uses the version server to rollback only the affected files.

Summary: Dependencies at the operating system level are established by rules based on BackTracker [47]. These rules are vulnerable to false positives and false negatives. While Taser [24] and RFS [52] recover from intrusions removing the effects only in corrupted files, RETRO [25] removes the values written by $A_{intrusion}$ and replays the forward system calls while their input changes. If $A_{intrusion}$ is identified properly, then RETRO does not have false positives.

The operating system level services are vulnerable to attacks inside kernel because they only audit the system calls. Attackers can compromise the recovery system because the log daemons are installed in the machine where attacks are performed. The recovery guarantees are limited by the system administrator capability to detect the attack and pinpoint the intrusion source. System administrators must avoid false positives to prevent legitimate data losses. However, remove false dependencies can take a while because the low abstraction level creates bigger dependency graphs and logs.

2.2.3 Recovery at Database Level

A vast number of database management systems (DBMS) support recovery by loading a snapshot (or full-backup) of the database, possibly patched with blocks of data modified since the snapshot was taken. However, this approach does not distinguish between malicious and legitimate requests. The recovery approach we are interested in the document is applied to databases similarly to what was

seen in Section 2.2.2 for operating systems. While the operating system dependencies are established by the system calls, the database dependencies are established by transactions. First, we define the main dependencies in the database systems. These rules are used by most of the recovery services for databases and applications (Section 2.2.4).

Compromised transactions are determined from an initial set of bad transactions using read and write rules. "Transaction T_j is dependent upon transaction T_i if there is a data item x such that T_j reads x" [36] and T_i performs the latest update on x. Transaction dependency is transitive. "A good transaction G_i is suspected if some bad transaction B_i affects G_i. A data item x is compromised if x is written by any bad or suspect transaction" [36]. This dependency chain is broken if a transaction performs a blind write, i.e., the transaction writes an item without read it first.

However, legitimate transactions can have different outputs even when their first execution were not tainted. For example, a malicious transaction can remove a data item which the following transactions would read and then write other data items. Since user mistakes are often deletes due to wrong query arguments, this is a relevant issue. Xie *et al.* [54] propose to track the transaction that deleted the data items keeping a copy of deleted data items in a separated database table. To add the dependencies from the deleted data items, the *Structured Query Language* (SQL) statement is performed in the original and delete tracking tables.

The dependency rules require to extract the read and the write set of each transaction, i.e., the set of data items that each transaction read or modifies. The following proposals use different methods to extract these sets and restore the tainted data items.

ITDB [26, 36, 45]: Intrusion Tolerant Database (ITDB) performs intrusion recovery in databases using compensating and supports *runtime recovery*, i.e., the database service remains available during the recovery process. ITDB uses the generic set of dependency rules mentioned in the beginning of Section 2.2.3 and extracts the read and write set parsing the SQL statements.

During the record phase, ITDB audits the read and write sets of each transaction. Most relational *Database Management System* (DBMS) only keep write logs. Therefore, Liu *et al*. [26] propose a pre-defined per-transaction type template to extract the read set of parsed SQL statements. This approach is application dependent since updates in application queries require updates in their templates.

At recovery phase, ITDB initiates a set $O_{tainted}$ with the intrusion source data items. Then, it reads the logged read and write sets of each transaction from the intrusion moment to the present. For each transactions, ITDB keeps the write set until the transaction commits or aborts; if the transaction commits after reading some data item that belongs to $O_{tainted}$, ITDB adds the data items in the transaction write set to $O_{tainted}$ and the transaction must be compensated. The compensating of a transaction reverts the effects of the original transaction. It performs the inverse modification of the original transaction to restore the previous values. Repaired entries in $O_{tainted}$ are tracked to prevent compensating of later transactions from restore a repaired data item to its version after the attack.

After this process, the latest legitimate value of $O_{tainted}$ entries is recovered.

If the intrusion propagation is faster than the recovery process then the recovery phase is endless because the damage will spread through new transactions. To prevent damage spreading, ITDB blocks the read accesses to the data items in $O_{tainted}$. Since identification of $O_{tainted}$ requires log analysis, Liu *et al.* propose a *multi-phase damage container* technique to avoid damage spread through new requests during the recovery phase. This damage containing approach denies the read access to the data items were written after the intrusion. Then, during the recovery phase, it releases the data items that were mistakenly contained. This approach speeds-up the recovery phase and confines the damaged data items. Moreover, it supports *runtime recovery*. However it decreases the system availability during the recovery period and degrades the performance.

An alternative approach concerns the throughput asymmetry between the recovery and the user flows. The asymmetry can be neutralized if the repair request priority is increased. Then, the availability is not compromised anymore but users may read tainted data and propagate the damage slower.

The ITDB architecture includes an IDS. The IDS is application aware and acts at transaction level. Liu *et al.* propose isolation in terms of users: when a suspicious transaction is reported by the IDS, every write operation from the suspicious user is done in isolated tables.

The ITDB does not perform transaction replay during the recovery phase. Therefore, it ignores that legitimate executions can be influenced by the updated values. Liu *et al.* propose a theoretical model [55] based on possible workflows and versioning. However, predict every possible workflow requires extensive computational and storage resources.

Phoenix [27]: Phoenix removes the intrusion effects using a versioned database. While Liu *et al.* [36] rely on templates of SQL statements and read the log in recovery time, Phoenix changes the DBMS code to extract read dependencies and proposes a runtime algorithm to check dependencies between transactions.

Phoenix performs every write operation appending a new row to the table. This new row includes an unique transaction id to support the restoration of previous row versions. Phoenix modifies the PostgreSQL DBMS code to intercept read queries during their execution and to extract the transaction id of each accessed row. The logged data is used to update the dependency graph.

At the recovery process, Phoenix identifies the set of affected transactions, $A_{tainted}$, from a root set of malicious transactions, $A_{intrusion}$, using the dependency graph. Then, it changes these transactions status to *abort* in the PostgreSQL transaction log. Since PostgreSQL, in serializable snapshot isolation mode, exposes only the row version of the latest non-aborted transaction, the row is restored and the effect of tainted transactions are removed.

Summary: Recovery systems for relational databases differ on their methods to track the read and write sets and to restore previous values. ITDB is application dependent because it requires pre-defined templates to parse the SQL statements. On the other hand, Phoenix is application independent but DBMS dependent because it modifies the DBMS source code and relies on the usage of

serializable snapshot isolation mode.

ITDB is records the previous versions in contrast to Phoenix which just records the transactions. The first requires more storage capacity to save versions, the second requires the knowledge of the compensating of each transaction and more computation resources during recovery to revert the tainted transactions.

The data item granularity affects the runtime performance overhead and the accuracy of dependency tracking. Coarser granularity, e.g., row, results in lower performance overhead but a higher probability of false dependence if two transactions read and write different portions of the same data item. Moreover, an attack can compromise just an independent part of the transaction and legitimate data is removed.

2.2.4 Recovery at Application Level

Web applications are the main type of application which is deployed in PaaS. These applications are usually composed of a three tier architecture: presentation tier, application-logic tier and data tier. The following works assume the data tier to be a database. Previous section works establish the dependencies between transactions using their read and write sets. However, they ignore the dependencies between transactions at application level. For example, an application can read a record A through a transaction 1, compute a new value B, based on A, and write the value B through a transaction 2. The application-logic tier is often state-less, the requests are independent and the database is the only mean of communication between requests (Section 3.2).

Data Recovery for Web Applications [28]: Goel *et al.* propose a recovery service that selectively removes intrusion effects from web applications that store their persistent data in a SQL database. Since each user request may involve multiple transactions, it tracks the user, the session, the request and the accessed rows. The proposal uses a tainting algorithm and compensating transactions.

During the record phase, a monitor logs each user request and the database rows and tables read and written by the transactions associated with it. Transactions are stamped with an id that establishes the replay order, since the database uses serializable snapshot isolation.

The recovery phase is as follows. First, the system administrator, using the logged data, identifies the malicious requests $A_{intrusion}$. Then, using a dependency graph, it determines the tainted requests. The dependency between transactions is established in a similar manner to the Section 2.2.3 but using table granularity instead of row granularity. Such coarse-grained approach may generate many false dependencies. Therefore Goel *et al.* use *taint propagation via replay*. Moreover, it proposes to modify the PHP-interpreter to reduce the false dependencies between transactions using a variable-level tainting. In other words, variables that read tainted rows or fields are also tainted; rows or fields written by tainted variables are tainted. This process increases the precision of the set of tainted requests. Finally, the compensation transactions of the tainted requests are applied in reverse serialization order on the current state of the database to selectively revert the effects of the database operation issued by the tainted requests.

POIROT [56]: POIROT is a service that, given a patch for a newly discovered security vulnerability in a web application code, helps system administrators to detect past intrusion that exploited the vulnerability. POIROT does not recover from intrusions but proposes a tainting algorithm for application code. During the normal execution, every user request and response is stored. The log of each request includes the invoked code blocks. After the attack discover phase, the software is updated to fix its flaws. POIROT identifies the changed code blocks and requests dependent from them during the normal execution. The affected requests are replayed. During the re-execution phase, each function invocation is forked into two threads: the updated e non-updated version [57]. Functions invocations are executed in parallel and their output are compared. If outputs are similar, only one execution proceeds otherwise the request execution stops since the request was affected by code patch. These concepts are used in Warp [29].

Warp [29]: Warp is a patch based intrusion recovery service for single server web applications backed by a relational database. Unlike previous approaches, Warp allows system administrators to retroactively apply security updates without tracking down the source of intrusion and supports attacks at user browser level. Warp is based on RETRO [25] *taint propagation via replay* approach and removes the intrusion effects using a versioned database. The Warp prototype uses PHP and PostgreSQL.

During the normal execution, Warp uses a client browser extension to record all JavaScript events that occur during the visit of each page. For each event, Warp records the event parameters, including the target *Document Object Model* (DOM) element. HTTP requests are stamped with a client ID and a visit ID to track dependencies between requests at browser level. On server side, Warp records every requests received and forwards the request to the PHP application. Since Warp uses PHP, an interpreted language, it records which files were used during the original request execution and records the non-deterministic functions. Warp stores the database queries input/output and tracks the accessed table partitions using a SQL statement parser. To conclude, the HTTP response is logged and packed with all execution records.

Warp includes a time-travel versioned relational database. Each row is identified using a row ID and includes a *start time* and *end time* timestamp columns that establish the row validity period. Warp reverts the intrusion effects, in a specific row, loading one of its previous versions. Warp supports concurrent repair using more two integer columns to define the begin and end of each *repair generation*. At repair phase, the current repair generation ID is incremented to fork the database. User requests are performed in the current generation while recovery requests are perform in the next generation. After replaying the requests retrieved until the beginning of the repairing process, the server stops and applies the remain requests.

During the repair phase, the system administrator updates the application software to fix its flaws. Then, Warp determines the requests used the modified source code files [56, 57]. These requests are the root cause of changes during the re-execution. To update the database and reflect the patch,

each user request is replay using a server-side browser and taint propagation via replay. The modified PHP interpreter intercepts non-deterministic function calls during the replay and returns the original logged value. Also, database read queries are replayed only if the set of affected rows is different or its content was modified. Write queries are replayed loading a previous version of the rows and replaying the SQL statement. Each row, which has a different result after re-execution, is now tainted and all requests that read the row are also marked to replay in the browser. Finally, the HTTP response is compared with original. If responses are different, the following dependent user interactions are replayed in the server side browser.

The server-side browser may fail to replay the original user request. The request may depend on a reverted action of the attacker. These conflict cases are queued and handled by users later.

Warp rewrites the SQL statements, which are used by the application to perform write operations in the database, adding four extra columns per table: start/end timestamp and start/end generation. However, these columns may be a considerable storage overhead. It also depends on a client browser extension to log and modify every request. Warp is designed for single machine applications: it does not support application deployed in multiple servers or distributed databases since versions are timestamp based.

Aire [30]: Aire is an intrusion recovery service for loosely coupled web services. It extends the concept of local recovery in Warp [29] tracking attacks across services. While Dare [51] aims to recover a server cluster synchronously using RETRO [25] in each node operating system, Aire performs recovery in asynchronous third-party services using Warp [29].

Aire prevents the recovery process from locking due to remote servers downtime. To achieve this goal, the pendent repair requests are queued until the remote server is recovered. Since clients may see a partial repaired state, Aire proposes a model based on eventual consistency [58, 59]. The model allows clients to observe the result of update operations in different orders or delayed during a period called *inconsistency window*, i.e., until the remote server recovers. Aire considers the repair process as a concurrent client. To repair key-value database entries, Aire creates a new branch [60] and re-applies legitimate changes. At end of local repair, Aire moves the current branch pointer to the repaired branch.

Like Warp [29], during the normal execution, Aire records the service requests, responses and database accesses. Requests and responses exchanged between web-services, which support Aire, are identified using an unique ID to establish the dependencies.

The recovery phase is as follows. First, the system administrator identifies the corrupted requests. The system administrator can create, delete or replace a previous request or change a response to remove the intrusion actions. Second, Aire creates a new branch, which will contain the set of changes. Third, Aire does a local repair of the application in a similar manner to Warp [29]. In contrast to Warp [29], starts the recovery process in remote servers if at least one of the requests or responses sent previously is modified. To do so, Aire sends a request to the source or destination of the modified message. If the remote server is offline, the repair requests are queued to be sent later. As repair

messages propagate between the servers to start successive repairing actions, the global state of the system is repaired. However, clients may see an inconsistent state during this process. Therefore, Aire applications must support eventual consistency.

The Aire approach using eventual consistency requires the developer to concern the conflict resolution. Moreover, Aire recovers third-party web-services, which must have an Aire daemon. Aire requires the system administrator to pinpoint the corrupted requests. Finally, Aire, as Dare [51], requires application downtime during the recovery process.

Undo for Operators [31]: Undo for Operators allows the system administrators to recover from their mistakes, software problems or data corruption in email services with file system storage. The design is base on “Three R’s: Rewind, Repair and Replay" [46] where operator loads a system-wide snapshot previous to the intrusion, repairs the software flaws and replays the user-level requests to recover a correct application state. In contrast to the selective replay approach, where only the tainted entries are reverted, the rewind approach reverts all database entries. On one hand, this approach requires to replay more requests. On the other hand, the approach does not require to determine which data items are tainted because every entry is reverted.

Undo for Operators proposes a proxy interposed between the application and its users. The proxy intercepts application requests. Since requests most be ordered to replay, Undo for Operators defines the concept of *verb*. Each protocol operation has its own *verb* class. A verb object encapsulates a single interaction (request/response) of the user and exposes an interface to establish the order between requests and their dependencies. However, the proposed architecture is protocol dependent. The proxy implementation only supports *Internet Message Access Protocol* (IMAP) and SMTP. A new protocol requires a new set of verbs.

During the normal execution, user requests are encapsulated into verbs and sent to a remote machine: the *undo manager*. The undo manager uses the interface of verbs to define its dependency, i.e., if it can be executed in parallel or must have a causal order with other request. The dependency is established per verb type depending from the operation and its arguments. Thus, the dependency mechanism is application dependent. For example, send email operations (SMTP protocol) are commutable and independent because the email delivery does not have ordering guaranties. On the other hand, the order of delete (expunge) and list (fetch) operations in the same folder is relevant and they are not independent. If two verbs are dependent, the second is delayed upon the first is processed. This method establishes a serialization ordering but it can create a significant performance overhead on concurrently arriving interactions and requires protocol knowledge.

The recovery phase strategy is as follows. First the operator determines the corrupted verbs and fixes their order adding, deleting or changing verbs. Second, the application is *rewind*, i.e., a system-wide snapshot is loaded to remove any corrupted data. Third, the operator patch the software flaws of the application. Finally, all legitimate requests started after the intrusion, $A_{legitimate}$, are re-sent by the proxy to rebuild the application state.

External inconsistencies may come out when the requests are replayed. These inconsistencies

are detected comparing the re-execution and the original responses. Different responses trigger a compensating action defined per verb to keep an external consistent state. Again, these actions are application dependent.

During the recovery process, Undo for Operators replaces the current system state by a system wide snapshot. Consequently, it does not support runtime recovery. Moreover, it relies on protocol knowledge to establish dependencies, compensating actions and to sort the requests during the normal execution and recovery phase. Therefore, any protocol change requires modifying the supported verbs. Intrusions can use corrupted requests which are not defined as verb classes and cause a system fail.

Summary: Goel *et al.* and Warp [29] establish dependencies using the request read/write set of the database and use taint via replay. Undo for Operators [31] establishes dependencies using the knowledge of the operations protocol. Unlike Goel *et al.*, Warp [29] and Undo for Operators [31] support application repair. Warp tracks the requests affected by the modified file. Undo for Operators replays every request using its proxy. While Goel *et al.* ignores external consistence, Warp [29] detects inconsistencies in responses and replays the user interaction in a browser and Undo for Operators uses compensating actions based on protocol-specific knowledge.

Their approaches to remove the intrusion effects are also distinct. Goel *et al.* uses compensating transactions to create a system wide snapshot, Undo for Operators loads a previous snapshot and Warp keeps the versions of each data item. If the tainted request are few, then Goel *et al.* and Warp have a significant advantage because they replay only the tainted requests. On the other hand, Undo for Operators requires less storage than the remaining options. Moreover, the knowledge of inverse transaction is required to create the compensation of transactions.

2.3 Chapter Summary

Previous subsections describe various services that use different approaches to recover from intrusions. The level of abstraction outlines the recorded elements. Intrusion recovery services at the operating system level record the system calls and the file system. At the database level they track the transactions. At the application level they track the transactions, requests and code execution (Table 2.1). The log at operating system level is more detailed but may obfuscate the attack in false positive prevention techniques. At database and application level, the log is semantically rich but does not track low level intrusions.

Most of services require the system administrator to identify the initial set of corrupted actions or objects (Table 2.1). The system administrator may be supported by an IDS. The alternative, proposed in Warp [29], tracks the requests which invoked modified code files. The identification of the actions or objects can incur on false positives and negatives due to system administrator mistakes. Tracking

the invoked code files requires to change the interpreter (JVM, Python, PHP) but avoids false positives and negatives.

The taint algorithm, which determines $O_{tainted}$, is performed statically using the first execution dependencies. Dependencies are recorded in a dependency graph or determined dynamically replaying the legitimate actions that have a different input in replay phase than in first execution. The later reflects the changes during the replay phase, therefore it is clearly better but requires storing the input of every action. An alternative proposed by Undo for Operators [31] sorts the requests, using the knowledge of the application protocol, and then loads a previous snapshot and replays the legitimate requests. This approach is possible because *every* legitimate request is replayed with a known order. The tradeoff between perform taint propagation via replay or replay every request is equivalent to a trade-off between storage and computation. In the first, the system must store every version of each data item while in the later system only stores the versions of each data item periodically. In the worst case, if all data items are tainted by the intrusion, the first approach will replay the same number of requests as the second.

Warp [29] supports application source code changes tracking the original code invocations and comparing output when the application functions are re-invoked. Undo for Operators [31] support application changes using application dependent compensating actions to resolve conflicts. Goel *et Al* [28] do not support code changes because the used taint via replay mechanism stops if the action input is similar. The remaining proposals do not support code change.

System	**Data logged**	**Intrusion identification data**	**Taint mechanism**	**Supports action changes**
[24]Taser	System call inputs	Tainted or intrusion source objects	Graph	✗
[25] [51] RETRO, Dare	System call inputs and outputs	Intrusion objects or actions	Taint via replay	✗
[26] ITDB	Read/write sets using SQL parsing	Intrusion objects	Set expansion (graph)	✗
[27] Phoenix	Read/write sets using DBMS modification	Intrusion actions	Graph	✗
[28] Goel *et al.*	User, session, request, code execution and database rows	Intrusion requests	Graph and taint via replay	✗
[29] [30] Warp, Aire	Client side browser interactions, requests, user sessions, invoked PHP files	Requests which invoked the modified source code files	Taint via replay	✓
[31] Undo for Operators	Requests	Intrusion requests or tainted objects	Application protocol dependencies	✓
Shuttle (this work)	User requests, session and read/write set using DBMS changes	Intrusion requests	Graph and taint via replay	✓

Table 2.1: Summary of storing and intrusion tracking options

System	Previous state recovery	Effect removal	Replay phase	Runtime recovery	Externally consistent
[24]Taser	Snapshot	load legitimate entries value from a snapshot	No		
[25] [51] RETRO, Dare	Snapshot	load legitimate entries value from a snapshot	Tainting via replay		
[26] ITDB	Transaction compensating	Compensate tainted transactions	No	✓	
[27] Phoenix	Row versioning	Abort tainted transactions	No		
[28] Goel *et al.*	Transaction compensating	Compensate tainted transactions	Tainting via replay		
[29] [30] Warp, Aire	Row versioning	Load previous entry version	Tainting via replay	✓	✓
[31] Undo for Operators	Snapshot	load snapshot	Replay all requests sorted by application semantics		✓
Shuttle (this work)	Snapshot	Load snapshot	Replay tainted requests sorting by their first execution	✓	✓

Table 2.2: Summary of state recovery options

At recovery phase, the intrusion recovery services remove the intrusion effects and recover a consistent state (Table 2.2). Three of the possible options to remove the intrusion are: snapshot, compensating and versioning. Versioning is a per-entry and per-write snapshot. This mechanism is finer-grained than snapshot and allows the reading of previous versions without replay the actions after the snapshot. However, the storage requirements to keep the versions of every entry in a large application can be an economic barrier. The usage of actions compensation requires the knowledge of the actions that revert the original actions.

To recover a consistent state, intrusion recovery services should replay the legitimate actions dependent from the intrusion actions (Section 2.2.1). While Undo for Operators [31] propose to replay all legitimate user requests sorted by an application-dependent algorithm, the remaining services, which perform replay, use tainting via replay to selectively replay only the dependent actions. The late approach may hide indirect dependencies [54] but recovers faster. Undo for Operators [31], replays every request generating conflicts that must be solved in order to achieve a consistent state. Warp [29] queues the conflicts for later solving by users. Proposals [26, 27, 29, 30] support runtime recovery (Section 2.2.1). This characteristic is required to support intrusion tolerance but allows intrusion to spread during the recovery period. To prevent that, ITDB [26] denies the access to tainted data. However, it compromises the availability during the recovery period.

3

The Shuttle Architecture

This chapter describes the overall system architecture of Shuttle and outlines its central functional components. The main design goal is to help CSP customers to recover from intrusions in their applications deployed in PaaS. We consider three actors: the CSP, which provides the platform, the *tenants*, who deploy their applications in the platform, and the *users*, who access the applications. Shuttle is a service designed to be offered by a CSP.

We introduce the main requirements in Section 3.1 and describe a generic PaaS architecture in Section 3.2. The remaining sections describe the architecture of Shuttle and discuss the main design choices.

3.1 Requirements

This thesis addresses the problem of providing an intrusion recovery service for applications deployed in PaaS. Our overall goal is to *make PaaS applications operational despite intrusions*. More precisely, we aim to create a service, named Shuttle, to help PaaS tenants to recover from the following problems in their applications:

- *Software vulnerabilities:* non-authorized users compromise state by exploiting software vulnerabilities that allow invalid requests to be executed.
- *Malicious or accidentally corrupted requests:* users, authorized or not, compromise the application state accidentally or intentionally issuing valid requests.

For instance, two common attacks that can be used to compromise application state consist in: (1) attackers stealing valid users' credentials and using them to access their data; and (2) doing a SQL Injection attack by mixing SQL meta-characters with normal input and doing otherwise invalid queries

to the database. Both attacks can be performed using apparently valid requests. Consequently, many prevention mechanisms fail to block them.

In order to achieve the above goals, the service shall meet the following requirements:

- *Remove intrusion effects:* Remove corrupted data at file system, database and application levels in the application containers and update affected legitimate actions.
- *Remove selected malicious actions:* Help tenant to track the intrusion producing the set of actions affected by an externally provided list of malicious actions.
- *Support software update:* After recovery, the application state has to be compliant with the new version of the software.
- *Recover without stopping the application:* Recover the application without exposing users to application downtime.
- *Determinism:* Despite concurrent re-execution of requests, the result of re-execution is the same as the result of first execution if the application source code and requests remain equal.
- *Low runtime overhead:* The recording of operations or state for recovery purposes should have a negligible impact in the runtime performance.
- *NoSQL database snapshot:* NoSQL databases will have to be extended to support database snapshots, in order to reduce the recovery time.
- *PaaS integration:* The source code of the application shall remains unmodified as much as possible. PaaS developers do not need to install or configure Shuttle. Shuttle is built in a generic manner and it is reused in each deployed application.

Shuttle shall *support software updates* to prevent future intrusions and allow operators to try new configurations or software versions without effects in the application behavior perceived by users.

3.2 Platform as a Service

PaaS is a cloud computing model for automated configuration and deployment of applications in a cloud infrastructure [1–4]. PaaS enables developers to develop and deploy web applications into production fast by abstracting many details of the underlying infrastructure. Developers access the infrastructure resources, such as storage, through a set of services. These services are often pay-per-usage. PaaS provides a deployment environment for a set of languages.

Applications are deployed in one or more application servers, e.g., Tomcat or NodeJS. *Containers* [5] hold these application servers and provide the required isolation level between the various applications. The word container is often used to refer to lightweight in-kernel resource (CPU, memory and device) accounting, allocation and isolation mechanisms like the *Linux control groups* [61]. These mechanisms isolate the process, network and file system used by applications that share the same operating system. They can run either directly on the host operating system or in a virtual machine.

In this document, we use the word *container or instance* to mean an isolated deployment unit that can be allocated from a resource pool by an orchestration engine. The deployment unit is created using an image and has storage attached. Therefore, our concept of container includes not only *Linux control groups* like systems but also bare metal servers and guest operating systems running on top of hyper-visors, e.g., Xen [62], KVM [63]. Containers are managed directly or through an orchestration or IaaS system (e.g., OpenStack [64], *Amazon Web Services* (AWS) *Elastic Compute Cloud* (EC2) [65], Eucalyptus [66], Omega [67]). Containers have one or more associated storage. When the container loads up, it loads an image onto its storage. The image contains, at least, the operating system and the PaaS system in order to deploy the application in the container.

In order to let Shuttle as generic as possible, we consider the following components of a minimal PaaS architecture (Figure 3.1):

- **Load balancer:** Routes user requests based on application location and container load.
- **Instance controller:** Collects the container metering data and performs the configuration, tear-up and tear-down of containers in the instance.
- **Cloud controller:** Manages the tear-up and tear-down of containers.
- **Metering and billing**: Retrieves the metering data from each container. The load balancer uses this information to perform request routing while the cloud controller automatically decides when to scale.
- **Containers:** The isolated environment where applications run.
- **Cloud Instances:** The guest operating systems or bare-metal machine where the containers run.
- **Authentication manager:** Provides user and system authentication.
- **Database instance:** A single DBMS shared, or not, between multiple applications. Most database middleware are built-on multiple containers to provide scalability and replication.
- **Authentication manager:** Provides user and system authentication.

CSP also deploy the database management systems in containers. Their data is accessed as a service by the developers. Most of the applications deployed in PaaS are designed to scale horizontally, i.e., to scale adding more containers. Therefore, the database and/or the session cookies often maintain the application state. The PaaS systems are often integrated with code repositories and software development tools reducing the time deploy of applications in cloud environments. Users may access the website connecting to the load balancer via HTTPS, which will decrypt the *Secure Socket Layer* (SSL) session and forward the unencrypted requests to application containers. As the traffic increases, the load balancer may become a performance bottleneck if the system does not provide enough resources to handle the user traffic.

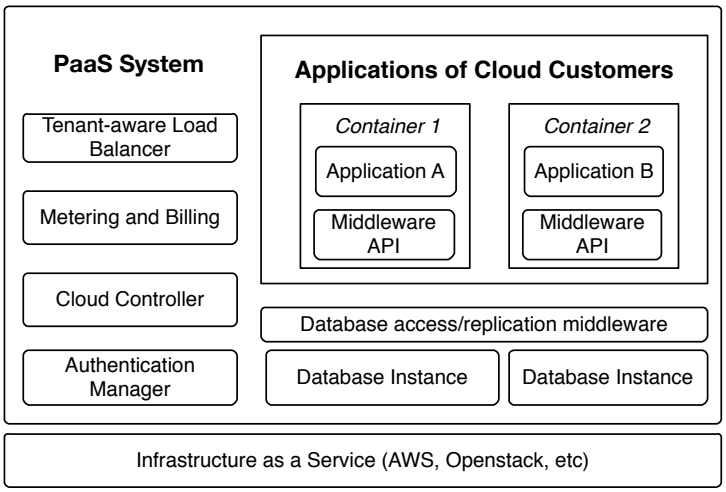


Figure 3.1: Generic PaaS architecture

We assume applications to store their persistent state only in databases. Shuttle's architecture can be extended to encompass object storage, for instance AWS *Simple Storage Service* (S3). We do not consider a possible state stored in the filesystem because PaaS applications are supposed to be scalable, thus the instances file system is frequently destroyed.

3.3 Shuttle Overview

Shuttle is an intrusion recovery service for PaaS. It recovers from intrusions on software domain due to software flaws, corrupted requests, input mistakes and corrupted data in PaaS containers (Section 3.2). While previous works (Chapter 2) aimed to recover applications supported by a single database, Shuttle targets PaaS applications deployed in multiple instances and backed by NoSQL databases. Since typical PaaS applications are designed to support high usage loads, our main contribution is a scalable intrusion recovery service that is transparent for application developers.

Shuttle is an automatic recovery mechanism based on the record-and-replay approach. Applications supported by Shuttle can operate in one of two states: *normal execution* and *recovery*. During *normal execution*, Shuttle records the data required to recover the application afterward: it does periodic database snapshots, logs user requests and database operations. When an intrusion is identified, tenants use Shuttle to recover their applications staring the recovery phase.

The processes described in Section 2 lead us to define *how to remove the intrusion effects* and *how to recover a consistent state*. During the *recovery phase*, Shuttle removes the intrusion effects creating a branch of the system execution in which it loads a snapshot that contains an application state before the intrusion began. It builds a consistent state by replaying (re-executing), in the new branch, the legitimate requests logged during the *normal execution*, performing either full or selective replay (Section 3.5.8). In the meantime, the incoming requests are executed in the previous branch. When ready, Shuttle sets the new branch as the single execution branch.

Shuttle aims to be integrated by CSPs into their PaaS architecture as a novel service. Services provided in PaaS are expected to be well-tested and available without setup because they are offered by CSP and shared by multiple tenants. Our approach hides the Shuttle implementation and operation within the database and load-balancing PaaS services. Shuttle components can be shared by multiple clients but the data of each client remains isolated. For sake of simplicity, we present Shuttle considering a single tenant implementation.

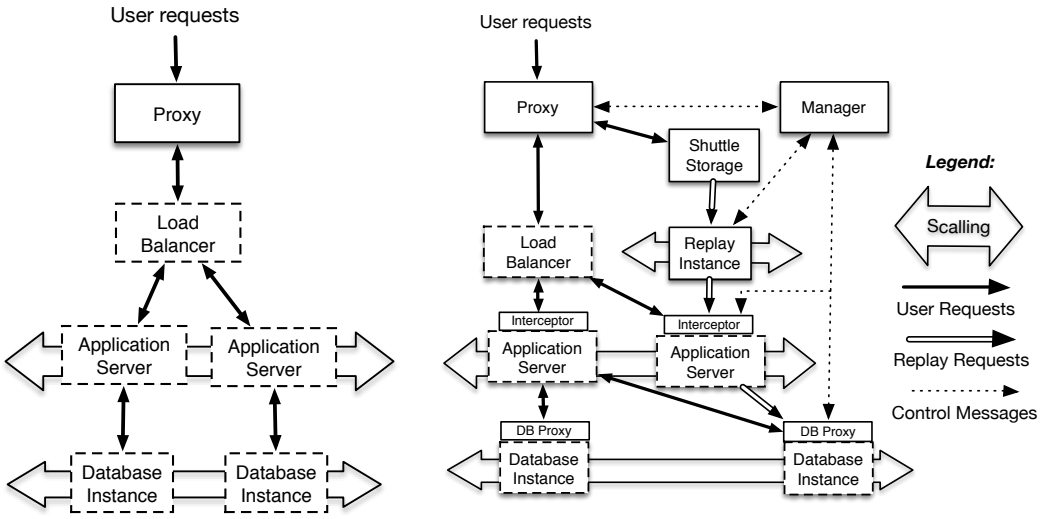
We consider a minimal PaaS architecture to let Shuttle as generic as possible. We consider a client-server model in which clients access applications using the HTTP protocol [1]. HTTP requests are received by a load balancer that forwards them to web/application servers, which access a shared database. PaaS components are represented with solid line in Figure 3.2, while Shuttle components are represented with dashed line. PaaS platforms with Shuttle have the following components:

- *Proxy:* Logs every HTTP user requests, adds an unique mark to its header and forwards it to the load balancer. The proxy functionality might be part of the load balancer but conceptually it is a different component.
- *Load balancer:* Routes requests to different application servers taking into account their load (part of the PaaS platform).
- *Application servers:* The application (or web) servers are the components of the PaaS platform that run the application logic. This logic uses a library to access the database service. Shuttle uses a *database client interceptor* mechanism in this library to log the data items accessed per request.
- *Database instances:* A set of database servers used to store the application persistent state. Shuttle includes in each instance a *database proxy* that logs the requests that accessed each data item and determines the dependencies between requests.
- *Shuttle storage:* A scalable storage component that stores requests, responses and metadata.
- *Manager:* Retrieves dependencies and coordinates the recovery process.
- *Replay instances:* A set of HTTP clients that read previously executed requests from the Shuttle storage and invoke the application servers to re-execute the requests during the recovery process. The manager coordinates the worker instances.

The *Shuttle storage* keeps the content of the user requests and responses. Although we do not consider this aspect in the architecture, this store can be replicated to a remote site to allow tolerating catastrophic failures in a datacenter.

We consider the Shuttle components to be part of the trusted computing base since their integrity and availability are critical to recover the application state. We assume that intrusions tamper the application data, which is stored in the database, not the snapshots neither the stored requests.

[1] Shuttle also supports HTTPS by ending the connections at the proxy.



(a) without Shuttle **(b)** with Shuttle

Figure 3.2: Shuttle service architecture:The dashed line components are part of the PaaS architecture. The proxy logs the user requests into the Shuttle storage. The manager coordinates the recovery process where the replay instances replay the user requests.

Unlike previous works, our design encompasses distributed databases (NoSQL). These databases are designed to scale horizontally. Therefore, Shuttle can also be scaled by adding more database instances.

PaaS offerings are supported by a computing infrastructure, often provided as a service (IaaS model), able to scale the application allocating new instances on-demand or automatically, to maintain the quality of service despite demand oscillations. This elasticity allows allocating replay instances and to scale the application to attend the requests issued by them during the recovery process. Due to the common pay-per-usage model, these resources are paid only when a recovery process occurs. The remaining cost of the service comes from storing client requests and database snapshots. Our design aims to optimize the available resources to reduce the recovery period and costs.

3.4 Normal Execution

Shuttle logs the data it needs to recover applications during the normal execution phase: user HTTP requests, application HTTP responses, database items accessed by each request and sequence of operations to each database item (Figure 3.3). In this section, we describe the normal execution phase following the path that a request takes to be processed.

The proxy intercepts all user HTTP requests, except those to static contents (e.g., images), and adds a new header field named *Shuttle Request Data* (SRD). Each SRD contains three subfields: *Request ID* (RID), which is an unique timestamp; *Branch* and *Snapshot*, which define, respectively, the database branch and snapshot (Section 3.5.2) and a *restraint* flag, which is used to support runtime recovery (Section 3.5.6).

The proxy also intercepts every application response, associates the response with the original

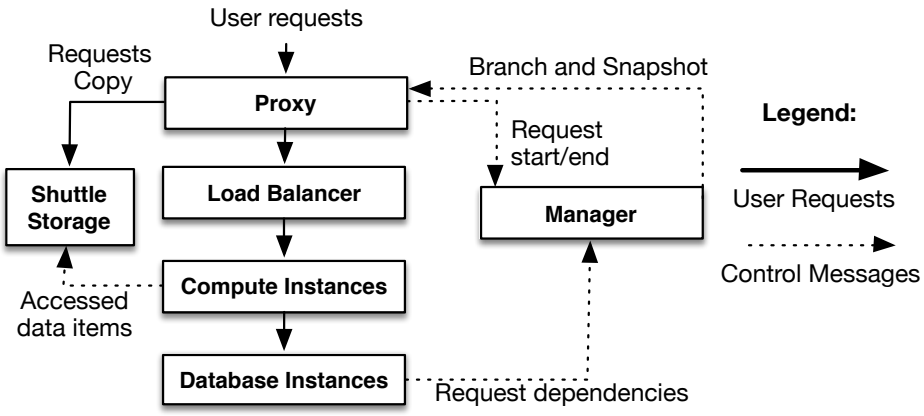


Figure 3.3: Interaction between components during the normal execution

request and adds a new timestamp to track the ending of the request execution. Requests, responses and their timestamps are stored in the *Shuttle storage* using asynchronous I/O, which permits the operations to proceed before the transmission has finished.

Requests are sent to the load balancer, which forwards the requests through the application instances according to their usage.

The application instances invoke the database service using the database client library. The database client library intercepts the operations, logs the accessed data items per request and stores this information in the *Shuttle storage*. The database invocation is tracked at client side because the database may not be available or operations may fail.

On each database instance, the database proxy logs the operations' RID and type. The sequence of operations to a data item defines its *operation list*. Periodically, each database instance iterates the operation list of every data item to establish the dependencies between requests. Shuttle also performs snapshots periodically. The snapshot operation stores a new version of data item on the next write operation (Section 3.5.2).

In summary, every request-response pair is timestamped and logged by the proxy, the application instances the accessed data items per request, the database logs the sequence of operations per data item. The sequence of operations of each data item is kept in the database instance in which the data item is stored. The remaining data is stored in the *Shuttle storage*, which can be located, or replicated, in a remote site to prevent catastrophic disasters rebuilding the application state using the requests and a previous snapshot. The manager retrieves, asynchronously, the requests' start and end timestamps, which are sent by the proxy, and their dependencies, which are collected by the database instances. Shuttle uses the information retrieved to generate the request dependency graph (Section 3.5.3).

3.5 Recovery

The intrusion recovery process consists of three steps. The first step concerns the intrusion detection, in which tenants detect intrusions, suspicious behaviors or software flaws. Tenants may use automated tools such as IDS [26] to detect intrusions. The second step is vulnerability management in which vulnerabilities are identified, classified and mitigated. This work assumes that tenants identify the malicious requests (the subsequence of actions $A_{intrusion}$ whereby the attacker compromises the application) correctly and modify or remove them. Alternatively, tenants can provide an updated and vulnerability-free software version (Section 3.5.1). In addition, Shuttle provides several methods to help tenants to identify the malicious requests: determine the set of requests that accessed a set of affected database entries after an estimated intrusion moment; group requests by user-session; compare database versions to check if the vulnerabilities are correctly mitigated.

The third step consists in removing the intrusion effects. Intrusions affect the application integrity, confidentiality and/or availability (Section 2.2). Recovery from confidentiality violations is out of the scope of this document. However, we argue that the design of the applications should encompass cryptography techniques which may reduce data relevance and protect the data secrecy [44]. Shuttle aims to recover applications from integrity violations, which often harm the availability. Shuttle can accomplish some of the goals of intrusion tolerance, keeping the application availability. Applications can keep providing a, possibly degraded but adequate, service during the intrusion recovery. Incoming requests are executed while the recovery process occurs without externalization to users (Section 3.5.6). In addition, Shuttle reduces the system downtime by reducing the time to recover when intrusions happen. Shuttle does not replace the intrusion prevention, detection and tolerance mechanisms, which are the primary lines of defense against attacks.

In order to remove the intrusion effects, Shuttle loads a database snapshot, which is selected by the tenant. The selected snapshot shall be previous to the intrusion moment in order to replace the value of every data item by a non-tampered value. Shuttle *manager* orders the PaaS controller to launch a new set of application instances and deploys an updated source code version, which may include code fixes. Then, the manager orders the database instances to load the selected snapshot (Section 3.5.5). The application is intrusion-less now that the snapshot is previous to the intrusion and the application is redeployed on new instances.

After, the manager initiates a set of *replay instances* to replay the legitimate requests of the sequence of legitimate actions that happen after the snapshot, $A - A_{snapshot} - A_{intrusion}$. The replay instances retrieve a list of requests to replay and get the requests HTTP package from the *Shuttle Storage* (Figure 3.4). Most PaaS systems scale automatically and horizontally, i.e., they increment or decrement the number of containers based on the measurements of the containers usage. Therefore, the application-logic and data tiers scale to attend the requests from the replay instances, increasing the recovery speed.

The database separates the versions used by the replayed requests and the new requests, pre-

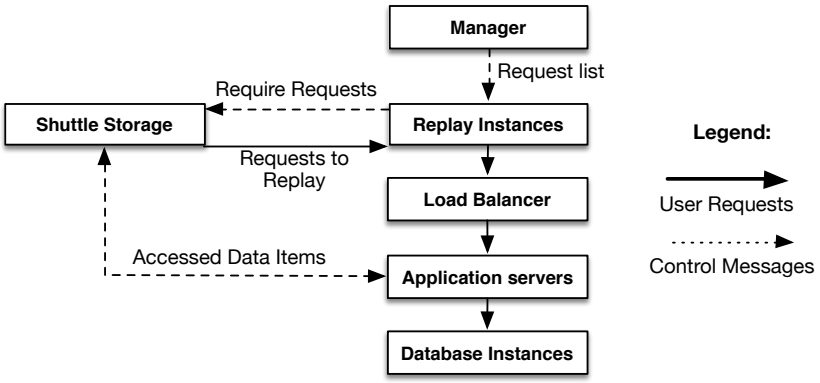


Figure 3.4: Interaction between components during the recovery process

venting the application from exposing a downtime. After the recovery process, the new requests are also forwarded to the recovered database version (Section 3.5.6).

The main version of Shuttle loads a previous database snapshot and replays every legitimate user request. An algorithm concerning selective replay is introduced in Section 3.5.8.

In the following sections, we discuss each of key process of the recovery phase in further detail.

3.5.1 Intrusion and vulnerability correction

The recovery process starts when intrusions are detected or the application software requires an update. Intrusion detection is out of the scope of this work. We assume that tenants, or system operators, detect one or more intrusions with the following sources:

1. User request (e.g. stolen user session)
2. External action: actions not logged by the proxy (e.g. ssh connection to the instances)

Attacks may:

1. Tamper the database (e.g. adding new entries)
2. Tamper the container (e.g. changing the deployed application in the container)

Shuttle supports the following actions to fix the exploited vulnerabilities:

1. Update the application software
2. Identify a set of tampered database entries
3. Add, modify or remove logged requests
4. Launch cleaned database or application server instances

Shuttle removes these effects of malicious actions redeploying the application in new containers and rolling back the database to a snapshot previous to the intrusion.

Attackers may use external actions to perform the intrusion, for instance gaining control of the instance to modify the database files. These actions are not recorded by Shuttle therefore they are not replayed and the application recovers a consistent state. We analyze several intrusion scenarios in Section 5.2.

If tenants update the application software, they have to ensure that the application's interface remains compatible with the requests that will be replayed. Alternatively, tenants may update the entries in the database and provide a script to modify the requests make them compatible with the new *Application Programming Interface* (API).

If the database is tampered using user requests, the tenant has to identify the malicious user requests. In addition,tenants can provide the set of suspicious database entries to Shuttle and it will resolve the set of requests that accessed the suspicious items after the estimated intrusion moment. Knowing the suspicious requests, the tenants shall use Shuttle to add, modify or remove the past requests to remove accidental or malicious behaves.

In summary, at the beginning of the intrusion recovery process, tenants shall ensure that:

1. The software is correct: previous flaws are fixed, its API is compatible with the requests and its behavior is the expected.
2. The requests, which are selected to replay, are legitimate and their dependencies are correct.
3. The estimated intrusion moment is previous to the intrusion moment (the selected snapshot is intrusion free).

3.5.2 Snapshot

Shuttle needs to remove intrusion effects. In Section 2.2, we presented two mechanisms to do so: record the data item values or compensate the malicious actions. The first makes a copy of the data item value at a certain instant t, implying more storage resources. The second applies compensating actions to each action over the data item value after the instant t, which requires more computation resources to invert every action after t. However, the compensation mechanism requires the knowledge of the actions that revert the effects of the malicious actions. Moreover, if a malicious action is not recorded, then compensation mechanisms do not revert its effects. Since the set of operations is unknown and Shuttle aims to remove all intrusion effects, we perform snapshots by recording the value of the database items at a certain instant t (first mechanism).

A snapshot is a complete set of versions of every data item in the system from which data values can be read but to which updates are not made. Snapshots save the application persistent state at a certain moment. Unlike the selective undo approach, which only reverts the tainted data items (Section 3.5.8), the full replay approach loads a snapshot previous to the intrusion instant. This approach reverts every database item and removes the effects of any action that occurred after the snapshot

creation.

The duration of the recovery process is mainly defined by the number of requests previous to the intrusion of the set, A_{before}. The snapshot mechanism avoids to replay every request from the beginning of the application, which can take too long. Shuttle requires not only a snapshot but also every action posterior to the snapshot instant. Therefore, Shuttle keeps every user request posterior to the oldest stored snapshot instant. The snapshot period defines the usage of storage and computation resources. We argue that tenants can balance the costs of storage and computation resources by specifying a policy to perform the snapshot. The policy shall consider the rate of requests, the data written per request, the expected time to detect the failure and the application capability to provide an possible degraded service during the recovery period.

Shuttle takes snapshots automatically and according to specified policies. It records the persistent state of the application, i.e., the database values, at a certain instant. The volatile state of the application, for instance its stack, is not stored as we consider the web servers to be stateless.

Performing snapshots in distributed databases is not trivial since snapshots have to be consistent with the user requests. We consider each user request may include multiple database operations, each of them to multiple database servers, without using transactions. Consequently, the sets of database operations of each user request cannot be aborted and do not have a global order. If Shuttle replays requests on a snapshot that contains part of the persistent state written by a request during its first execution, the replay will be inconsistent. The database must reflect the effects of a set of completed requests and not the results of partially executed requests. Therefore each snapshot shall be *global request consistent* containing either all or none of the database updates made by every request.

We define *request consistent global snapshot*: a snapshot is global request consistent if it records a state of the database which reflects the effect of a set of completed requests and not the results of any partially executed request. This concept derives from the notion of *transaction consistent global checkpoint*: a checkpoint is a transaction-consistent global checkpoint if it contains all or none of the updates made by a transaction [68]. Since most NoSQL databases do not support transactions, we extend the concept of transaction to *request transaction*. A request-transaction embraces all database operations performed due to the execution of a request. Unlike *Atomicity, Consistency, Isolation and Durability* (ACID) transactions, a request-transaction may not be possible to abort. In summary, Shuttle snapshots are request consistent: a snapshot contain all or none operations of a request.

Checkpointing algorithms for distributed databases can be classified as log-oriented and dump-oriented [69]. In the dump-oriented approach, the checkpoint is referred to as the process of saving the state of all data items in the database. In the log-oriented approach, periodically a dump of the database is taken and also a marker is saved at appropriate places in the log. When a failure occurs, the latest dump is restored and the operations on the log after the dump was taken is applied to the

dump until the marker is reached to restore the database to a consistent state [68]. We take the latest approach.

In addition, the snapshot mechanism shall be non-blocking: the processes shall not stop their execution while taking snapshots.

A straightforward way to take a request-consistent global snapshot is to stop processing new requests, waiting until the currently executing requests finish, then making a copy of each data item. However, this solution incurs on communication overhead to reach a globally inactive state and causes application downtime. Yet, this approach may fit applications that can be unavailable during a certain period, for instance, during a certain period of the night.

Kim and Park [70] propose an approach in which a coordinator broadcasts a checkpoint-request message to every database node. Each database node divides the transactions into two groups: before the checkpoint-request T_p and after T_f. Updates of transactions in T_p are flushed to the current database, while the ones in T_f are flushed in a *checkpoint area* (a temporary allocated storage area). When all transactions of T_p are done, the checkpoint area is updated with items updated by transactions in T_p but not by T_f. After, the rules of current database and checkpoint area are exchanged. The major drawback of this approach comes from updating the checkpoint area: the database is unavailable during the updating process.

Our solution leverages the existence of a single load balancer and, consequently, single proxy that adds a SRD field to every request. Every SRD contains a RID, an unique and incremental identification of each request given by the instant when the request is retrieved. Every database operation is identified by the RID of the source user request.

In order to create a snapshot, tenants define a future instant in time t when the snapshot will occur. The instant, named *Snapshot ID* (SID), identifies the request-consistent global snapshot. The manager passes the SID to every database proxy.

Database proxies use the SID to define the version of the data item used by the operations. Operations with RID lower than the scheduled snapshot instant (RID < SID) access the version before the snapshot. Otherwise, the operations access the latest data item version. This mechanism splits requests to accomplish a request-consistent global snapshot, and allows tenants to schedule snapshots without application downtime. Figure 3.5 illustrates the sequence of 7 database operations on the database item x and 3 snapshots (excluding the base snapshot).

In order to avoid to replay every database operation to obtain the snapshot, the snapshot mechanism shall create a database copy (dump). We avoid blocking the application to copy values using a copy-on-write and incremental method. When a data item is written for the first time in each snapshot, Shuttle creates a new version of the data item. Since a data item may not be written in every snapshot, e.g., $SID = 200$ in Figure 3.5, we associate a *version list* to every data item. A *version list* tracks on which snapshots the data item has been written. In conclusion, the snapshot is an incremental mechanism because it does not require to duplicate data.

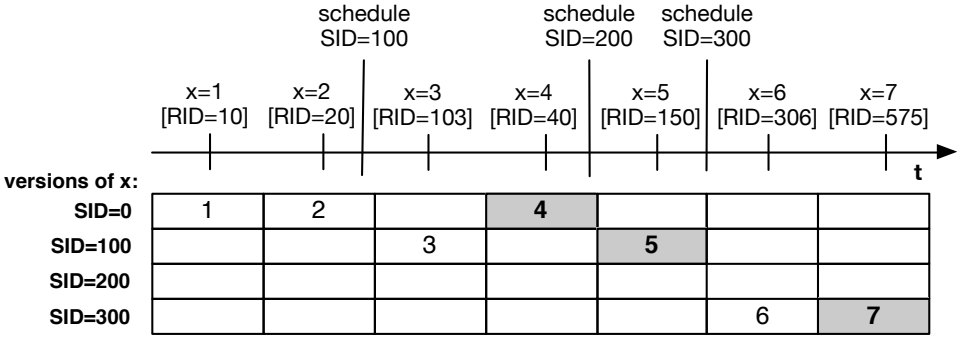


Figure 3.5: Versions stored in the database during a sequence of 7 operations and 3 snapshots. The final values of the stored versions are contained in filled squares. The tenant schedules 3 snapshots on SID: 100, 200, 300.

RID=10 (SID = 1)	RID=20 (SID=15)	Storage
Write A=10		A1=10
	Read A: A1==10	A1=10
	Write A=20	A1=10, A15=20
Read A: A1==10		A1=10, A15=20
	Read A: A15==20	A1=10, A15=20
Write A=11	*Completed*	A1=11, A15=20
Completed		A1=11, A15=20

Table 3.1: Concurrent requests: the snapshot instant is 15, the left request accesses data previous to the snapshot (A1) while the right accesses the latest (A15 or A1).

A snapshot might become inconsistent. For instance, Table 3.1 represents the execution of two concurrent requests. Their normal execution is consistent. A snapshot with SID=5 would contain [A1 = 11] and be a global request-consistent. However, if Shuttle loads the snapshot and replays the request 20, its first read operation reads A1 == 11 instead of A1 == 10.

This particular case happens when a request with RID greater than the snapshot instant SID read a version belonging to the snapshot SID and, after, a request with RID lower than SID overwritten that version. Storing a new version and adding a flag on the version list solves the problem. Nevertheless, we expect this to happen only in rare occasions.

Unlike the approach proposed by Kim and Park, our approach allows to record multiple snapshots keeping various data item versions and does not require to copy the transactions.

The value of SID must be known by every database instance before the execution of any request with $RID > SID$. If the RID was determined by incremental request counter, then Shuttle would need to analyze the request rate and estimate the SID value. However, the request rate can vary and the snapshot would fail. Notice that our mechanism does not require clock synchronization because the RID is defined by the proxy timestamp and tenants can schedule a snapshot defining a future time instant. The period between the scheduled moment and the present must be bigger than the communication delay between the manager and the database instances. Consequently, we assume the communication between the manager and database proxies is synchronous: the messages are delivered within a fixed time.

3.5.3 Dependency Graph

An application execution can be modeled as a set of actions and a set of objects. Actions read and write objects. An action A is dependent from an action B if A reads an object's version written by B.

Requests must be replayed in a consistent manner to obtain a consistent application after the replay phase. The request replay order must ensure that if the requests, application semantics and initial database values are the same, then the final database values are equal. For this propose, the dependencies between actions shall remain consistent: if during the first execution an action A becomes depends on an action B by an object O, then during the replay phase A shall read the object O only after B updates the object O. Otherwise, A may read a version different than the original version.

Previous proposals, for instance *in* [28], leverage the request serialization provided by snapshot isolation in relational DBMS to order the operations to replay. In contrast, *Undo for Operators* [31] uses the application protocol knowledge to establish the dependency between requests and order them. However, accesses to NoSQL databases are not globally serialized. Moreover, the data items accessed during the replay phase may change due to updates to the application semantics, request modification or multi-threaded execution. At last, the application semantics is unknown in advance since we want to support any application deployed on PaaS. Taking that into account, we propose a novel approach.

Shuttle tracks the dependencies between actions in a *dependency graph*. A *dependency graph* consists of nodes that represent requests and edges that establish dependencies between them (Figure 3.9). Dependencies between requests are established using the following rules: a request R_A is dependent upon request R_B if there is a data item x such that R_A reads x and R_B performs the latest update on x before the read operation by R_A. Dependencies are transitive except when requests perform blind writes, i.e., requests write items without reading them first [36]. Therefore, the dependency graph is a mixed graph, if there is a dependency between A to B, then there may be a dependency between B and A.

Previous solutions for relational databases extract the dependencies using a pre-defined, manually-created, per-transaction type template [26], or change the relational database management system code to extract read dependencies [27]. In contrast, Shuttle uses the database proxy to log the database accesses. Periodically, each database proxy traverses, in background, the *operation list* of each data item to collect the new accesses and to generate the dependencies between requests. The Shuttle manager processes the dependencies to update the dependency graph. An alternative approach is to pull the dependencies from each database node only before the recovery process and generate the dependency graph when needed.

The above method may lead to *false positives*, i.e., to flag dependencies that do not exist. For instance, a request may read a data item but not use it to compute the written value, so there is no real dependency. Although tracking variables used by each request during its execution might solve this particular case [28], it would require modifying the code interpreter (e.g., Zend Engine for PHP),

which would constrain Shuttle to a set of specific languages. As our approach uses the dependencies to group the requests that can be executed concurrently, false dependencies imply a performance penalty but do not cause data loss or inconsistent state. On selective replay mode, the dependency graph is used to determine the tainted requests and the request that need to be replayed. Again, false dependencies only harm the performance.

When tenants use the dependency graph to determine the set of malicious requests, $A_{malicious}$, they shall take into account that false dependencies may lead to consider legitimate operations as malicious and, consequently, cause data loss.

Complex queries on a relational database may lead to *false negatives*, i.e. a dependency exists but is not detected. For instance when a read operation would have been executed on a deleted data item if this data item had not been deleted before the request execution [54]. Therefore, legitimate transactions may have different output even when they were not affected by malicious execution during their original execution. Since user mistakes are often delete operations due to wrong query arguments, this is a relevant issue.

In contrast with SQL queries that access the data items that match a query, the *create, read, update and delete* (CRUD) interface of most key-value stores specifies, in a deterministic and apriori manner, the data item that will be accessed. Shuttle logs every access, even when the data items do not exist, keeping the *operation list* of the deleted data items to track further operations.

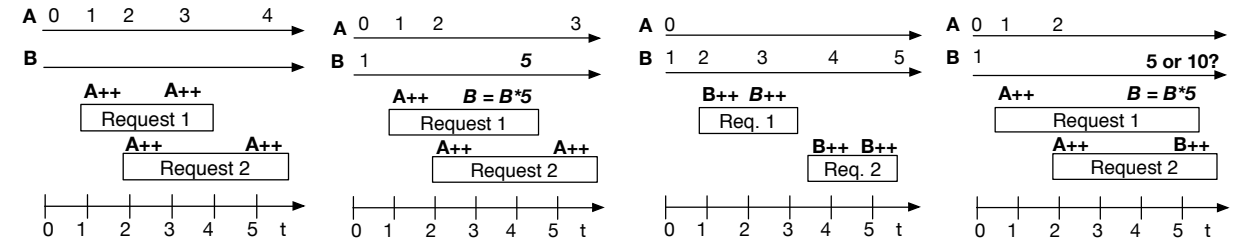
Shuttle can not replay requests synchronously, i.e., waiting for the response to the previous request before sending the next. To replay the requests synchronously would not have only performance degradation but also lock the replay phase because requests, which have been originally executed in concurrently during the normal phase, may be depend on each other. Therefore, Shuttle replays requests asynchronously and, hence, concurrently. Two requests are executed concurrently if they are dependent from each other. For instance, Figure 3.6a represents the first execution of two requests that increment the variable A. The $Request1$ depends on $Request2$ and vice versa.

Yet, re-execution of concurrent requests is not deterministic. User requests are processed concurrently using multi-threaded servers and the system messages, including database requests, do not have a delivering order. Therefore, the execution order of two concurrent requests is unknown. To deal with this issue, our novel approach uses the *operation list* to turn the re-execution of concurrent requests deterministic. An *operation list* is a sorted list that records the operations to a data item. During the replay phase, the operations to a data item must follow the order established by is operation list. For instance, in Figure 3.6a, the operation list of the data item A is: $[Req1 : Get, Req1 : Put, Req2 : Get, Req2 : Put, Req1 : Get, Req1 : Put, Req2 : Get, Req2 : Put]$. Req. 1 and req. 2 are replayed concurrently but the result is consistent because the order is established by the operation list.

During the recovery period, intrusions are removed and the application code is updated. This may cause requests to access different data items than in the first execution. Requests may not access the same sequence of data items or read/write the same content. If an operation contained in the

operation list is not performed, the following operations to the data item are blocked and the request fails. To address this problem, at the end of each request execution, the *database client interceptor* fetches the list of data items accessed by the request on its first execution and compares them against the ones accessed during the replay process. The database client library invokes the *database proxy* with the data items that have not been accessed to unlock the operations of the remaining requests.

For instance in Figure 3.6b, the $Request1$ has a different replay execution performing $B = B \times 5$ instead of incrementing A. The second operation of req. 2 is delayed until the end of the req. 1 because it succeed the second operation of req. 1 in the operation list. After the execution of req. 1, the database client interceptor unlocks the second operation of req. 2.



(a) Ordered by the operation list **(b)** Operation unlock **(c)** Consecutive requests **(d)** Conflict

Figure 3.6: Replay two requests with different re-execution

During replay there may be non-deterministic situations, whenever an access is not contained in the operation list. The most complex scenario during the replay is when two requests, originally executed in parallel, access different data items comparing with their first execution, establishing a new dependency. The result is unpredictable. Consider the possible re-execution in the Figure 3.6d where the req. 2 increments B simultaneously with req. 1 performing $B = B \times 5$. The result is unpredictable because the req. 1 may write before or after req. 2. Since both requests did not access the data item B during their first execution, the operation list does not establish an access order. Therefore, the req. 1 and req. 2 may execute on a arbitrary order. The order of these requests is as deterministic as if during the first execution: the operation of *req. 1* can execute before, between or after *req. 2*.

A naive solution would be to detect the new dependency during the replay process, stop the process and start a new replay process in a new snapshot, including the new dependency.

Brown *et al.* [31] propose the concept of *verb* (Section 2.2.4). A verb object encapsulates a single interaction (request/response) of the user and exposes an interface to establish the order between requests and their dependencies. However, tenants shall know the applications' operations to create the verbs defining: a commutativity test, an independence test, a preferred-ordering-test and an application-defined action to handle a inconsistency if the operation fails. Since Shuttle shall support any PaaS application, the applications' semantics are unknown in advance. Therefore, this solution is not adequate.

A sorted-log, in which the accesses are sorted, for instance by RID, would establish that operations

must have a strict incremental order. However, operations with smaller RID than the previous are aborted. For instance, the second operation of req. 2 in Figure 3.6a would be aborted.

An alternative solution consists on sorting the requests per *start-end order*, instead of using the dependency graph. A request starts only after all requests with end lower than it ends. Dependencies between requests remain correct, since they are constrained by the *operation list*. Thus the parallel requests are ordered and replayed in a similar manner to the first execution. Two serial requests can have distinct re-executions: if a request starts after the end of the previous. For instance in Figure 3.6c, req. 1 and req. 2 can have distinct re-executions.

If two operations are re-executed concurrently, then their order is as deterministic as if they happen during the first execution. For instance in Figure 3.6d, the operation of req. 1 $B = B \times 5$ is executed in parallel with the operations $B++$ of req. 2. The order of these requests is as deterministic as if during the first execution: the operation of req. 1 can execute before, between or after req. 2.

In order to turn more operations of the replay process consistent with the first execution, we can leverage semantic reconciliation, as *in* Dynamo [58]. The case represented in Figure 3.6d is equivalent to a concurrent update where two parallel writes are performed on distinct database instances. Each request writes a distinct version resulting in conflicting versions of an item. Developers use the application-assisted conflict resolution interface to merge the versions (reconciliation) [58]. In this case, the following read operation would access the values written by the latest operation. For instance, if the latest is req. 1, then it choose between 1 and 2. If the latest is req. 2, then it choose between 1 and 5. This solution can produce a consistent output.

In summary, unlike previous solutions, Shuttle orders the requests using their start and end instants and constraining the operations to the order established on the *operation lists*. This approach allows requests to access new data items during the recovery process and to replay concurrent requests.

3.5.4 Clustering

Despite Shuttle's capability to replay concurrent requests, one of the main challenges of Shuttle is to reduce the recovery period. We assume that critical software flaws and intrusions can be detected in a short period of time, from seconds to one week. If a fault exists during a longer period, then the application may tolerate a longer recovery phase because the recovery process used by Shuttle does not require application downtime (Section 3.5.6). Still, we want recovery to take a fraction of the time elapsed since the snapshot from which recovery starts (e.g., if the snapshot was taken a week before, we want recovery to take much less than that period).

We address this problem grouping the requests into *clusters*. A cluster is a set of requests that have dependencies between them but not from/to requests in other clusters. Clusters are created when the recovery is about to start by inspecting the dependency graph. Since clusters are independent, they are executed concurrently by different *replay instance* without synchronization. Requests within

the same cluster, are performed in start-end order (Section 3.5.3). Given that more requests are executed concurrently, Shuttle launches more application servers and database instances to process the replayed requests. Therefore, the replay phase throughput is bigger than the during first execution and the recovery time is minimized. This mechanism is applicable if the graph dependencies remain unchanged during the recovery phase, i.e,. every replayed operation is contained in the operation list but not all operations in the list must be replayed.

Taking the above in account, we define two replay approaches: *serial replay* and *parallel replay*. The first considers every request in the same cluster. The later uses the dependency graph to group the requests in independent clusters. Both approaches replay the requests in start-end order, supporting concurrent requests 3.5.6. In contrast to *serial replay*, *parallel replay* allows to perform more requests in parallel but it does not support new dependencies during the replay phase. Therefore, *parallel replay* requires that tenants ensure that the dependencies between requests do not change during the replay process. Since the dependencies between requests often remain constant and novel dependencies are easily detected, we consider *parallel replay* represents a significant advantage for CSP. These approaches are compared in Chapter 5.

3.5.5 Instance Rejuvenation

PaaS systems launch instances/containers and deploy applications or databases on them. Attackers may exploit vulnerabilities in the instances configuration to affect the service integrity, confidentiality or availability. For instance, an attacker may explore the shellshock vulnerability in the GNU's bash shell of out of date instances.

An effective technique to remove intrusion effects and restore the application availability is to terminate compromised containers and launch new containers. We name this approach as *instance rejuvenation*. A similar approach is used in proactive recovery systems for Byzantine fault tolerance. Castro *et al.* [20] propose a mechanism that recovers the replicas of a system periodically even if there is no reason to suspect that they are faulty. This mechanism aims to prevent an attacker from compromising the service by corrupting a quorum of the replicas without being detected. We extend this approach to PaaS to remove possible intrusion effects in containers, even if there is no reason to suspect that they are affected by the intrusion.

Shuttle interacts with the PaaS controller rejuvenate instances when they are compromised and a new recovery process begins. This process launches new instances. The PaaS controller initializes the new instances with updated container images and deploys an updated version of the application code or database, which may include updates to fix discovered flaws or prevent future intrusions. Shuttle copies the snapshot selected by the tenant to new database instances. Requests are replayed on the novel instances while the incoming requests are processed by the old instances, perhaps with a degraded integrity constrains. This mechanism keeps the application available during the recovery process. After the recovery process, the old instances are terminated.

We assume new instances to be intrusion-free since tenants or CSPs can update the image and the image is installed on an empty persistent-state. This approach fits the concept of automatic deployment applications in PaaS. Applications for PaaS platforms are designed to scale horizontally so the number of application instances can be dynamic.

In addition, the instances can be instantiated in a remote site to recover from catastrophic disasters [42]. Snapshots, database operation lists, application code and requests can be replicated to a remote site. If they are available, then Shuttle can launch new instances on a remote datacenter, deploy the application code, load the snapshot and operation lists in the database instances and replay the requests. This is a log-based recovery process [71] that allows to recover the application integrity and availability.

This process can also be used in a proactive manner to renew instances to remove unknown intrusions [20, 41] or to test new application versions with user requests to compare its results against the previous version, using the branching mechanism (Section 3.5.6).

Tenants are responsible for ensuring that request dependencies are correct and the API of the updated code version is compatible, or for providing a script to update each request to the new API. Moreover, the selected snapshot must be consistent according to the specification of the updated version or every request executed since the application begin shall be replayed.

3.5.6 Runtime Recovery

Applications shall remain available during the recovery process, perhaps with a degraded behavior, without exposing downtime to users. To do so, Shuttle considers each recovery process defines a new branch, a model inspired in versioning systems such as git [60].

A *branch* is a sequence of snapshots. Snapshots are analogous to *commits* in git. Each snapshot represents a set of versions of every data item in the database at a certain instant. Each recovery process creates a new branch forking a previous branch on a snapshot chosen by the tenant, either explicitly or implicitly (by indicating the initial intrusion instant, selecting implicitly the preceding snapshot). When a new branch is created, a new snapshot is also created on the new branch. Incoming user requests access only the data of the previous branch keeping the application available, while replayed requests access the created branch without compromising the availability of the application. If Shuttle launches new database instances, then the new branch is created in the new instances and write operations occur in the new instances. Read operations occur in the previous instances until the first write operation of the accessed data item in the new instances.

A branch contains a sequence of snapshots but a snapshot can only belong to a single branch (Figure 3.7). Each snapshot represents a possible version of the data item. A novel data item version is created only when the data item is written for the first time during each snapshot. Consequently, the data item may not have a version for each snapshot. Shuttle keeps a list of the versions in which each database item has been written (Section 3.5.2).

For instance, in Figure 3.8, a data item x may have the following sequence of versions on its version list: $[A, B, C, D, E]$. If x has not been written in snapshot E, the version E would not exists and the

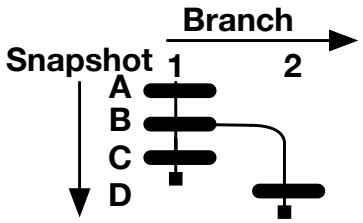


Figure 3.7: Tree model: 2 branches and 4 snapshots: branch 1 contains the snapshots A, B, C; branch 2 contains the snapshot D;

latest version of x would be D. However, the snapshot D has been compromised so it is not part of the current branch (branch 3). The latest non-tampered version of x is the version B. If version B does not exists, then the latest version is A.

We define the concept of *branch path*: a Branch Path of a certain branch is the sequence of snapshots between the current snapshot and the root snapshot. A Branch Path of a certain branch defines the versions available to operations that belong to that branch. The branch path of branch 3 in Figure 3.8 is {E, B, A}. The one of branch 2 is: {D, C, B, A}. When a branch is created, its branch path contains the its initial snapshot and the sub-sequence of snapshots in the branch path of the branch of the forked snapshot that are equal or previous to the forked snapshot.

The version accessed by an operation is defined using the branch path of the operation's branch and the version list of the accessed data item: operations read the latest version present in the *version list* and in the *branch path* and write the latest version in the branch path. Therefore, a new version, referring the initial snapshot of the new branch, is added to the version list on the first write operation to each data item during the replay.

This mechanism maps the operations to the correct versions and isolates the multiple, perhaps simultaneous, attempts to recovery the application without compromising the exposed application behavior. During the recovery process, users access the, perhaps corrupted, old branch loaded in the current computation and database instances. Therefore, the application remains online, perhaps with a degraded behavior, without exposing downtime to users.

At recovery time, the manager sends the new *branch path* to every database instance. The new incoming users access the, perhaps corrupted, old branch while the requests being replace access the new branch. Therefore, the application remains online, perhaps with a degraded behavior, without exposing downtime to users.

At some point, when the recovery is finishing, the user requests have to start being issued to the new branch. To do so, after replaying the requests, the proxy flag *restraining* is set and every new request is marked with the *restrain* flag. Database accesses marked with *restrain* are delayed. After replaying the requests retrieved during the recovery process, the proxy sets the new branch in the subfield *branch* of SRD of the new requests, the *restrain* flag is disabled and the database nodes are notified to proceed the accesses. This mechanism delays the processing of some requests, but this has typically a duration of seconds, compared with a recovery process that may take many minutes or even hours.

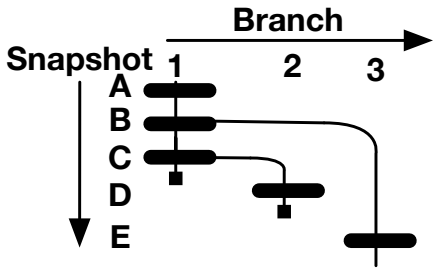


Figure 3.8: Tree model: 3 branches and 5 snapshots: branch 1 contains the snapshots A, B, C; branch 2 contains the snapshot D; branch 3 contains the snapshot E.

This mechanism ensures the recovery phase to be finite. However, if the rate of requests being replayed is much higher than the rate of new requests, then the requests retrieved during the replay phase are also replayed without restraining new requests. Consequently, the restrain phase is shorter and required only to change branch.

While Aire [25] used a branching mechanism to perform a recovery process in various systems simultaneously, we propose the mechanism to isolate user accesses from the recovery process. Our model allows the tenants to select any snapshot as base to a new recovery process and create snapshots in different branches. Applications can contain multiple branches simultaneously. Figure 3.8 represents an application with 3 branches: the branch 1 is the initial application branch where the tenant made three snapshots (A, B and C). After detecting an intrusion, the tenant considered that snapshot C is non-tampered and initiated a recovery process based on it creating the branch 2. Afterwards, the tenant made one snapshot (D) on branch 2. However, the snapshot C is tampered. So the tenant initialized a novel recovery process based on snapshot B creating the branch 3. In this scenario, the tenant would be unable to recover its application without the branching model. Since tenants may fork a new branch not only from the most recent snapshot. Therefore, the latest non-tampered version of a data item may not be its latest version.

Inactive snapshots and branches, for instance snapshot D and branch 2 in Figure 3.8, can be deleted to reduce the used storage resources. In addiction, tenants can use the branching mechanism to test their intrusion recovery procedures in background, i.e, without exposing users to test issues.

If an intrusion happens during the replay phase, then its effects are stored in the branch of incoming requests. If the intrusion is detected before the restraining flag is set, then the malicious requests are not replayed in the new branch. Otherwise, tenants shall start another recovery process.

3.5.7 Non-determinism and consistency

Shuttle provides an API to handle nondeterminism and inconsistency cases.

An application is called nondeterministic if two subsequent executions with the same user input cannot be guaranteed to have the same have the same final state and outputs. Five of the main

sources of non-determinism in PaaS applications are: shared memory, thread concurrency, random number generation, timestamps and message exchanging.

We assume requests to be independent thus they do not share memory and concurrent threads are independent. The API of Shuttle provides a deterministic random number generation and a timestamp. It uses the RID, which is a timestamp set by the proxy, as timestamp and pseudo-random number seed, so the replay of a request will use the same random numbers and timestamp. We consider a single timestamp per request to be enough for most applications. This mechanism is language independent. User requests and database accesses are ordered in a deterministic way using the operation list. Shuttle provides the following API for the application developers:

1. *getTimestamp():* returns the timestamp (RID) set by the proxy (*long*).
2. *getRandomGenerator():* returns a random number generator that has RID as seed.

An important aspect of a recovery system like Shuttle is the application consistency seen by users. For instance, if an user does an action based on data written by a malicious action, which result of the user action replay is consistent. Since users have a non-deterministic behavior, they may have to be notified if a recovery took place and their data was modified.

Since Shuttle is not tied to the application semantics, the actions to compensate the recovery process changes are unknown before the application is created. In addition, the application may contain client-side code, e.g., Javascript, that processes the application responses. For instance, a recover process reorders a list of items. The client-side code may sort the items so the list is seen ordered by users. A replay process taking into account the client-side consistency is proposed in [29].

Shuttle does not execute requests that returned an error in the first execution. We assume that requests are synchronous so users are immediately notified of the error and do not expect that the request will succeed in future. Similarly to other works in the area [31], we assume that these cases are compensated by the user when they happen. As only requests that did not return an error are replayed, Shuttle considers an inconsistency when a request returns an error or a response is different during replay. Shuttle provides the following API for the application programmer to define how inconsistencies are dealt with (Shuttle calls these functions in case they are launched by the tenant):

1. *preRecover():* invoked before the beginning of the recovery process.
2. *handleInconstency(request, previous response, new response, previous data items, new data items, action):* invoked when there is an inconsistency.
3. *postRecover(statistics, old version, new version):* invoked after the end of the recovery process.

The first function allows tenants to perform a set of actions before the beginning of the recovery process, such as notifying the operations team or taking a new snapshot. The second function takes as input the operation that caused the inconsistency as well as the response and keys accessed during the normal execution and during the recovery process. It also takes as argument the action to take.

Currently we consider three possible actions: 1) ignore the inconsistency; 2) notify the user of the inconsistency; 3) execute another request. This function is invoked, for instance, if a response during the replay is different than the response on the first request execution. Using the *postRecover* function, the tenant has access not only to the statistics of the recovery process but also to an interface to compare the database values before and after the recovery process and the application responses, before exposing the data to the users. Tenants can use this interface to notify their customer to verify their data.

Besides its users, an application may also interact with external services. We simplify the problem by considering that applications only obtain inputs from external services, disregarding the issue of outputs. The problem is treated in [30, 31]. Brown *et al.* [72] models each external service as a recoverable application. During the recovery phase, an external service can also be recovered if its input is distinct. Aire [30] proposes to initiate a recovery process in the external service and handles the inconsistencies of this process.

3.5.8 Full and Selective Replay

We propose two approaches for intrusion recovery: full replay and selective replay. Full replay consists in replaying every request done after the snapshot. Executing many requests takes considerable time, so this approach is adequate for intrusions detected reasonably fast after they happen, e.g., a few days.

Selective replay (Section 2.2.1) re-executes only part of the requests so it is faster than full-replay. However, it requires tenants to provide a set of malicious actions (i.e., requests) $A_{intrusion}$. This set is used to deduce the set of tainted requests $A_{tainted}$. A request is said to be tainted if it is one of the attacker's requests or if it reads objects written by tainted request [24, 26, 27].

Tainted requests can also be determined by Shuttle considering the tampered data items and an estimated intrusion moment. Selective replay approach loads only the previous versions of the tainted objects, $O_{tainted}$, and replays only the legitimate operations, which were tainted, $A_{tainted} \notin A_{intrusion}$, to update the application persistent state. Selective replay, as compensating actions, does not remove the effects of unlogged actions because their dependencies are unknown.

In [25, 28], the set of tainted operations, $A_{tainted}$, is determined using *taint propagation via replay*. To do so, they load a previous version, from a snapshot, of the objects in $O_{intrusion}$. Then, the actions, which are dependent from the restored objects, are replayed and their output objects are updated. The forward actions, which depend on the updated objects, are also replayed while their inputs are different from the first execution. The propagation is done thought the output of actions with different execution. Unlike these approaches, Shuttle does not store the input and output of every action, i.e., database operation. Shuttle proposes an approach in which the requests are replayed, at least, until the first snapshot after the selected snapshot. Consequently, the application semantic must remain unchanged, i.e., the same request and same input must perform the same write operations. Otherwise, the dependencies between requests are unpredictable and the tainted requests can not be determined. An approach that allows to update the application semantics is proposed in [29]. We

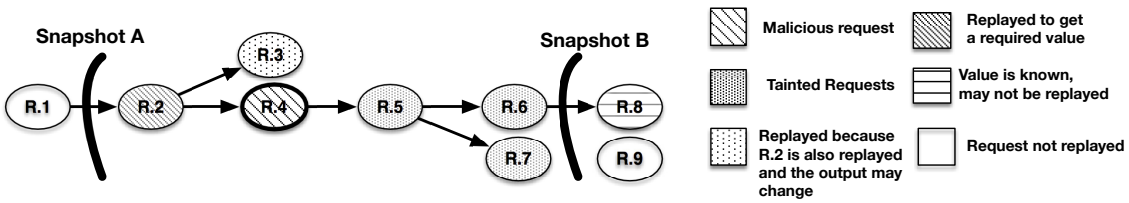


Figure 3.9: Dependency graph: $R.1$ is previous to a snapshot A; $R.3$ is dependent on $R.2$, which is replayed to get the read values; $R.4$ is a malicious request; $R.5, R.6, R.7$ are tainted; $R.8$ may not be replayed; $R.9$ is independent of the rest

consider storing all versions of a data item has prohibitive storage costs for enterprise applications.

For instance, consider the dependency graph of Figure 3.9, in which every request reads a data item and writes a new value on the same data item. The request 4 was identified as a malicious request. Therefore, requests $5, 6, 7, 8$ are tainted. Since Shuttle does not keep every version of the entries, the value read by request 4 is unknown. In order to get this value, Shuttle must replay the req. 2, which wrote the value read by req. 4. The value read by request 2 is known because Shuttle performed the checkpoint A. Since the application semantics remains the same and its input is known, req. 3 does not need to be replayed. Requests $5, 6, 7$ are replayed since they depend on the malicious req. 4. Values read by request 8 are known due to checkpoint B. Therefore, req. 8 may not be executed if the value of the data items remains the same. Shuttle performs *taint via-replay*: if a request writes in a data item which were not written previously, then the requests which read or write that data item, are also replayed. For instance, the req. 9 may read a data item written by the req. 4 during the replay but not during its first execution.

The selective replay process is as follows (full replay is simpler so we skip it):

1. *Determine the malicious requests $A_{intrusion}$.* Based on initial data such as user session compromised or data items accessed or other criteria, the tenant determines the requests $A_{intrusion}$ used by the attacker to compromise the application. For instance, $A_{intrusion} = \{R.4\}$ in Figure 3.9.

2. *Use $A_{intrusion}$ to determine the set of tainted requests $A_{tainted}$.* For each request in $A_{intrusion}$, traverse the dependency graph in causality order and add these nodes to $A_{tainted}$ (in the figure $A_{tainted} = \{R.5, R.6, R.7, R.8\}$).

3. *Get the requests needed to obtain the values read by $A_{tainted}$ and their effects.* Instead of storing the input and output of every action or versions of every data item, we propose to replay the actions which $A_{tainted}$ depends on. The data item value is known at the snapshot instant so the algorithm transverses the graph in inverse causality order from each request in $A_{tainted}$ and stores the requests in A_{replay} ($A_{replay} = \{R.2\} \cup A_{tainted}$). A_{replay} is expanded by traversing the graph from each of its elements on causality order to determine the requests which can be affected by the re-execution of A_{replay} ($A_{replay} = A_{replay} \cup R.3$). Requests subsequent to the

first snapshot after the latest malicious request may not be repeated as the data item version is known (version read by $R.8$ is stored in snapshot B).

4. *Determine the replay order.* The set A_{replay} is sorted on non-clustered *start-end order*.

5. *Load the previous data item versions* Shuttle loads the version in the selected snapshot of the data items read by the requests in A_{replay} and written by $A_{malicious}$.

6. *Replay the requests* Requests in A_{replay} are replayed. If an access is not contained in operation list, then a new dependency is established and the requests that accessed the data item during the first execution are also replayed as in *taint propagation via replay* [25]. For instance, $R.9$ is replayed if it reads an item written during recovery process but not during normal execution.

Shuttle does not require generating a dependency graph in non-clustered full replay mode. The dependency graph is required in the case of clustered full replay to identify the independent clusters of requests and on selective replay to determine the tainted requests. We use the database operation lists to create the dependency graph and to order the execution of parallel requests without knowledge of the application protocol.

In summary, the selective replay approach reduces the number of requests to be replayed during the recovery process but implies that the application remains unchanged and does not revert the actions performed by unlogged requests.

3.6 Chapter Summary

Shuttle recovers from security intrusions loading a previous snapshot and replaying the legitimate requests. It uses database snapshot and clustering to reduce the recovery time. Shuttle leverages the pay-per-usage model of PaaS to provide a cost-efficient and fast recovery service instantiating the replay instances and more application containers on demand during the recovery process.

Shuttle proposes two approaches to perform replay: selective replay and full replay.

	Clustering	Non-Clustering
Selective	✗	✓
Full	✓	✓

Table 3.2: Shuttle Replay modes

The full replay approach supports parallel re-execution of requests that belong to independent clusters (clustering). Clustering is not supported on selective replay because the *taint propagation via replay* defines the set of requests to replay at running time. Clustering is not supported with selective replay because taint propagation via replay defines the set of requests to be replayed in runtime.

The decentralized applications are more vulnerable to failures because of the single proxy architecture. However, we argue that future architectures can consider replication of the proxy, load balancer, Shuttle Storage and database.

4

Implementation

This chapter addresses the main decisions adopted regarding the implementation of the intrusion recovery system Shuttle. Shuttle is supposed to be implemented by the PaaS providers since it requires modifications to the PaaS system and database service.

4.1 Adopted Technologies

In order to implement the proposed work, we evaluated several technologies taking in account the requirements of the problem and the performance, scalability and easiness of implementation in a production mode PaaS provider service. The first Shuttle prototype was implemented in Python. The prototype of a simple application and the proxy allowed to analyze the requirements of Shuttle. The compact code of Python was great for code readability and rapid prototyping. However, despite the stackless variants of Python, the global interpreter lock limits Python to a single active thread per process. Since all modules of Shuttle are multi-threaded and their performance is critical to support medium and large-scale systems, Python was not appropriated. The selected language needs to be likely to run faster than Python and to have better concurrency and network libraries.

C or C++ languages are likely to have a better performance than Python because they are compiled. However, the development time can be considerably larger due to its low level. Java has a higher abstraction level than C but lower than Python. To argue about the performance differences between Java and Python, we would need to develop a version of Shuttle in Python and another version in Java. However, the proxy prototype using Java has a bigger throughput and lower latency than the one implemented using Python.

Shuttle has a distributed architecture and each module shall process various requests concurrently. Therefore, we also considered languages, such as *Erlang*, *Go Lang* and *Scala*. They facilitate

the writing of concurrent programs that share the state by communicating. Moreover, the actors model [73], native in Erland and available through frameworks as Akka [74] to Scala, could simplify the implementation and improve the performance.

Java is still the most used language in enterprise environments and it is compatible with most of PaaS. The selected database is implemented in Java (Chapter 4.1.2). In addition, Java has the *Non Blocking IO* (NIO) library that provides event-driven and asynchronous communication via network.

We chose to implement the Shuttle prototype in Java. However, the large number of concurrent tasks and asynchronous message passing communications turned the development of the prototype using Java extremely complex. Moreover, its concurrency model and network libraries have an abstraction level lower than desired to archive a fast development and good performance.

Therefore, during the development of the prototype, we concluded that *Scala* with *Akka* could be a better option than Java. It would be likely to simplify the development of the distributed system and improve the performance. However, rebuilding the prototype in a different language would also take too long. Therefore, we kept Java. In addition, the proxy performance could be improved using a C or C++ implementation, such as HAProxy [75].

Shuttle is built of several modules that communicate and coordinate their actions. We choose to use a messaging protocol instead of *Remote Procedure Call* (RPC) (such as Java *Remote Method Invocation* (RMI)). The message passing protocol should emphasized simplicity, performance and low overhead. It should also define data structures and service interface easily.

Plain text protocols are communication protocol whose content representation is intended to be read by humans. For instance, the *Simple Object Access Protocol* (SOAP) [76] specifies rules for using XML to package messages. Despite the heterogeneity and easiness of debug of plain text protocols, the text encoding and message structure has a significant overhead. As opposed, binary protocols are intended to be read by machines. The advantage of compactness translates into smaller messages and faster transmission and interpretation than plain text protocols. The capability of describe data structures using an *Interface Description Language* (IDL) and generate the source code in various programming languages to generate and parse the stream of bytes is also important to reduce the period of implementation and support transparent interaction between multiple programming languages. To cope with these requirements, we selected a binary protocol with IDL.

Apache Thrift [77] and Google's Protocol Buffer [78] are two of the current binary communication protocol that fit these requirements. These protocols are similar, the main difference is the first offers a stack implementation for RPC calls. The exact performance differences between them can only be measured benchmarking the two possible implementations. We choose Protocol Buffers to implement our prototype.

4.1.1 Platform as a Service

Shuttle is implemented as a service in PaaS framework. Since we can not modify the implementation of CSP solutions, such as Google App Engine [7] and Amazon Web Services [10], we chose an

open-source PaaS framework. The framework has to meet the following requirements:

1. *Open-source:* to support updates and modifications
2. *Support to add new containers:* to add new compute, database and replay instances.
3. *Contain a load-balancer:* to distribute the requests after the proxy
4. Extensible to support a new database management system
5. Deployable on OpenStack and AWS
6. Support for Java Applications

We consider the auto-scaling capability as optional since Shuttle may invoke the PaaS manager to create new application instances, database instances and replay instances. However, the capability to monitoring the containers usage during the recovery period turns the replay process faster and cost-efficient by adjusting dynamically the required resources (Chapter 5.3).

We require the PaaS system to be deployable on OpenStack [64] and AWS. Due to the costs of a public cloud service, the prototype is tested in a local cloud supported by OpenStack and later on a public cloud AWS.

We chose AppScale [11] to implement our prototype. AppScale meets the requirements except it does not support OpenStack nether supports the required database (Chapter 4.1.2). Therefore, we contributed for AppScale open-source project adding the support for both. AppScale supports auto-scaling monitoring the proxy and nodes: if one of the servers queue contains more than 5 requests or if the node usage exceeds the 90%, then it creates a new container and deploys the application. There are many alternatives being actively developed. The main open-source systems are Openshift by RedHat [9], AppScale [11], Apache Stratos [13], Cloud Foundry [12], Cloudify [79] and Solum project of OpenStack [80].

4.1.2 Database

Shuttle could be implemented in PaaS supported by most of known databases, including relational (SQL) databases (Database instances in Figure 3.2). However, previous projects encompass relational databases [28, 29] and PaaS applications are often supported by NoSQL databases. Shuttle is the first intrusion recovery system using replay considering NoSQL databases.

NoSQL databases are designed for extremely large data sets, hundreds or thousands of million entries. Most of the architectures of NoSQL databases claim to scale horizontally near linearly, i.e., adding twice the data means to add twice the nodes. To do so, the data of NoSQL storages is partitioned across multiple servers, for instance, by a range of keys or using consistent hashing [81]. Therefore, NoSQL stores can compensate the overhead imposed by Shuttle distributing the data across the nodes, scaling horizontally instead of vertically.

Unlike relational databases, NoSQL databases do not guarantee ACID properties. One of the main differences between the NoSQL storages is their approach to preserve consistency or availability during the network partitions. The CAP theorem states any networked shared-data system can have at

most two of the three desirable properties: consistency, availability and tolerance to network partitions [82].

NoSQL databases support new data structures, which are more flexible than the schema of relational databases:

1. *Column-oriented:* The data is organized in a multidimensional persistent sorted map with a large number of key-value pairs within rows.
2. *Document-oriented:* The format of the values is a JSON or JSON like document. Documents are organized in collections. The document attributes can be included in the query.
3. *Key-value:* Similar to a map where the values are opaque and accessed by an unique key.
4. *Graph:* Heavily linked data with multiple relations.

The evaluated alternatives are summarized in Table 4.1.

Type	Name	Language	API	Replication	Consistency
Column	HBase	Java	Avro, REST, Thrift	Master-Slave	Strongly consistent for a single row within a datacenter. Across rows is eventual consistent
	Cassandra	Java	Cassandra Query Language	Peer-to-peer	Depends on the selected number of read and writes
Document Oriented	MongoDB	C++	CRUD	Master-slave	Strong Consistency for a single row (default)
	CouchDB	Erlang	CRUD	Master-slave	Multi-Version Concurrency Control
Graph	Neo4J	Java	Cypher Query Language	Master-Slave	ACID using master. Updates to slaves are eventual consistent by default
Key value	Memcached	C	CRUD	None	The client selects the correct shard
	Voldemort	Java	CRUD	Peer-to-peer	Many-writer eventually consistent system: vector clocks and versioning

Table 4.1: Available No SQL databases

HBase and Cassandra follow the Google Big Table column-oriented database [81]. HBase has master-slave architecture and provides get, put, delete operations but also scan, server-side atomic operations and atomicity on row-level writes. Cassandra has a peer-to-peer architecture based on Dynamo [58]. The consistency of the operations is determined per-operation basis by the number of read and written replicas. Strong consistency requires to read/write a quorum while on eventual consistency the storage system guarantees that if no new updates are made to the object, eventually all accesses will return the last updated value. [58]. Cassandra resolves conflicts using the timestamp and a last-write-wins policy.

MongoDB and CouchDB are two of document-oriented stores. Their API allows to CRUD documents. MongoDB has master-slave architecture: one master per shard (a partition of the key-space) and the shard's slaves are eventual-consistent. Therefore, there are no conflicts. On other hand, CouchDB records any changes as a version of the document and allows conflict resolution via programmatic merge.

Graph stores such as Neo4J target a specific kind of applications.

Memcached and VoldemortDB are in-memory distributed key-value stores. Memcached does not provide a replication mechanism by default and it is often used to cache web pages. Like CouchDB, VoldemortDB is an eventual consistent store that accepts asynchronous concurrent writes.

The correct NoSQL database depends on the particular application, which has different size of data sets, complexity, rate between writes and reads, consistency requirements and methods to access the data. Column-oriented is beneficial for applications that must access a subset of values. Key-value structure is beneficial for applications that retrieve entire values.

We selected VoldemortDB [83] to implement Shuttle. Voldemort is an open source implementation of Dynamo [58], which is the base of DynamoDB provided on AWS. Voldemort is a key-value store developed and in used by Linkedin [84]. Voldemort has a put, get, delete, update (CRUD) API so we avoid the delay of parsing complex queries. Voldemort does not allow range queries, i.e., the user can retrieve only one value each time, so data items accessed by them are known before the request execution and, consequently, we expect fewer false dependencies (Section 3.5.3).

Voldemort accepts asynchronous concurrent writes and treats the result of each modification as a new and immutable version of the data. Versions of the data can conflict if two or more replicas are updated concurrently during a network partition. A network partition occurs when a failure causes the system to be partitioned in multiple sub-systems and two nodes of the system cannot communicate. When the network partition is healed, Voldemort uses the vector clock of each version to determine the causality between those versions [58]. A conflict exists if two versions do not have a causality relation. Voldemort resolves the conflicts during the following read operation. The conflict is solved is application-assisted: the application reads both versions and based on its semantics, the application chooses the correct version. We leverage the semantic reconciliation to solve distinct parallel replay with different execution (Section 3.5.3).

Voldemort keeps the persistent state on a local transactional database: BerkeleyDB, MySQL or an in-memory key/value data structure. It also allows to choose the serialization protocol, for instance: Java Serialization, Avro, Thrift and Protocol Buffers, which is also used by Shuttle as message passing protocol. Since Voldemort is open-sourced therefore we can modify its implementation to include the Shuttle requirements. We used the release 1.9.0 of Voldemort backed by BerkeleyDB and serialized using Protocol Buffers.

On an earlier stage, we considered and attempted to implement Shuttle on MongoDB. However, MongoDB is implemented using C++, does not support conflict solving and it extends the CRUD API with further complex operations such as scans. A future work may concern the implementation on a

column-oriented database, such as Cassandra.

The *Shuttle Storage* stores for each request: the HTTP request, HTTP response, the accessed keys and the start and end instants. Since an application is expected to retrieve hundreds or thousands of million requests, the data set stored in Shuttle Storage is expected to be extremely large. The size of each data item is expected to be on dozens of kilobytes. The write operations are frequent while the read operations occur during the recovery process. Each data item is written twice: once to add the request, response and start/end timestamps and once to add the accessed keys. The storage must be available during the recovery process and may be replicated to a remote site to prevent catastrophic disasters. Conflicts may occur within a data item: one version containing the request/response, the other containing the accessed keys. Therefore, eventual consistency is tolerated if the database management system is able to solve conflicts within the data item. At last, the fields of each data item are known and immutable.

Taking into account the above requirements, we selected to implement the prototype using Cassandra [85] as Shuttle storage. Cassandra keeps the versions per-column so it can resolve conflicts within the data item. In addition, it allows to choose the number of read and write servers. Due to the simple content format and the required operations, most of distributed databases, including Amazon's DynamoDB, Google's Cloud Datastore, fulfill the defined requirements.

The external storage should be protected, at least, against attacks to integrity and confidentiality. If the integrity of at least one request is affected, then Shuttle can not replay the requests previous to the most recent affected request and the application is unrecoverable if a snapshot following that period does not exists. For sake of simplicity, we ignore the security features of the Shuttle storage in this implementation as we consider the Shuttle storage to be part of the trusted computing base.

4.2 Normal Execution

Shuttle can operate in one of two states: *normal execution* and *recovery*. During normal execution, Shuttle collects dependencies between requests, stores the accessed data items, sets the correct branch to write the data item values and performs snapshots. Figure 4.1 summarizes the messages exchanged between Shuttle's modules during the normal phase. Shuttle identifies each user HTTP request with an unique SRD and identifies all database operations of each request with its SRD. The database operations are logged and sent to the manager, which generates the dependency graph. In this Section, we describe the normal execution phase following the path that a request takes to be processed.

4.2.1 Proxy

The proxy retrieves all HTTP user requests and adds the SRD to their headers. The SRD contains the following fields:

1. RID (long).

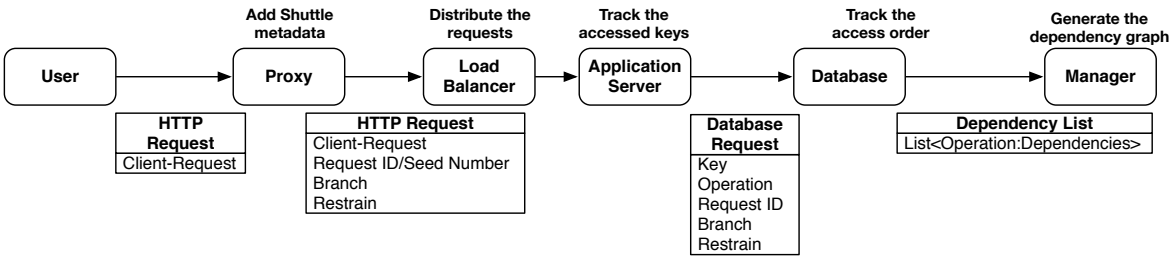


Figure 4.1: Interactions between components during normal execution

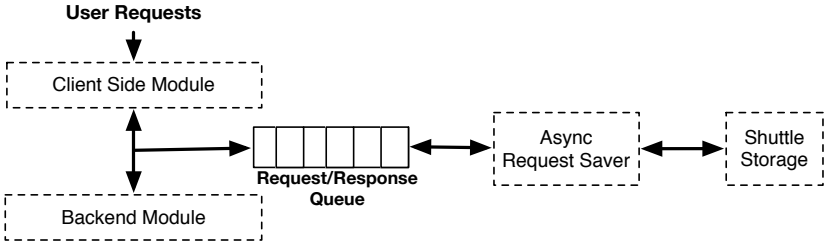


Figure 4.2: Proxy internal modules

2. Branch: the branch accessed by the request (short).

3. Restraint: to support branch change during the recovery phase (boolean).

The proxy could be implemented by modifying an existing open-source proxy, e.g., HAProxy or Nginx. They are well tested in production and implemented in C. Moreover, they are likely to perform better than a prototype using a higher-level language, such as Java (Section 5.3.1.2). However, for sake of expected simplicity, we implemented a new HTTP proxy using Java. Nevertheless, implementing most part of the HTTP protocol specification in an efficient manner using Java ended up to be a complex task.

The proxy is made of three parts: the client-side module, the backend module and the asynchronous request saver (Figure 4.2).

The client side module retrieves HTTP requests, parses their content and modifies their headers. We used the NIO library of Java to implement a TCP server. The server retrieves user requests and modifies their header (Algorithm 1). The values of *branch* and *restrain* are defined by the Shuttle's manager while the RID is a timestamp of the proxy instance. Java provides timestamps with a precision of millisecond. This precision limits the proxy performance to one thousand requests per second. Therefore, we used a counter to identify the same millisecond, up to 1000 requests per millisecond (1 million requests per second). The precision of the timestamp weights on the network and storage overhead. The RID is also used as a timestamp for the application and as a pseudorandom number generator, so the request generates always the same sequence of non-repeating numbers. The fields of SRD represent a fixed overhead of 35 ASCII characters, corresponding to 35 bytes, in every request header.

Proxy's TCP client threads send the requests to the load balancer. We use a fixed size thread pool to associate each HTTP response to the correct HTTP request. The thread that retrieves, processes and forwards the request to the load balancer, blocks until its response is retrieved. When the re-

sponse is retrieved, the Proxy associates a *end-timestamp*. A future work shall implement the proxy as a fully asynchronous proxy. To do so, the application server shall include the SRD in the responses. Since the delay of creating a new TCP connection to the load balancer is considerable, our implementation keeps the TCP session with the load balancer and implements the HTTP keep-alive specification. HTTP keep-alive is a standard that allows a single TCP connection to send and receive multiple HTTP requests/responses, instead of opening a new connection for every request/response pair.

Algorithm 1: Proxy

Input: received user HTTP request
Result: user HTTP request with modified header
1 **Initialization:** *establish a HTTP connection to the load-balancer*
2 $package \leftarrow$ Read TCP package from client
3 $request \leftarrow$ Parse $package$ to bound HTTP request
4 $SRD \leftarrow$ Get Shuttle's state: $id, branch, restrain$
5 Add SRD fields to request's header formated as:
ID: id
B: $branch$
R: $restrain$
6 Send $request$ to load balancer
7 Add SRD and $request$ to $queue$
`/* Retrieve response */`
8 $package \leftarrow$ Read TCP package from load balancer
9 $response \leftarrow$ Parse $package$ to bound HTTP response
10 $endTimestamp \leftarrow$ get current system time
11 Send $response$ to client
12 Add $endTimestamp$ and $response$ to $queue$

Shuttle proxy stores $requests$, $responses$, $end - timestamp$ and SRD in the Shuttle storage. If the data would be sent synchronously to the storage, then the response delay would increase. Therefore, we implemented a message queue (Figure 4.2). The client-side and backend module add the data as a message in the queue. Worker threads dequeue the messages and store the data in Cassandra. This allows asynchronous behavior: requests can proceed before the transmission has finished. The worker threads are wake when the queue reaches a defined threshold or a timeout period expires. The message queue is implemented as a *synchronized list* in Java.

4.2.2 Application Server

The Shuttle implementation in application servers shall meet two architecture requirements: log the database accesses per request and include the requests' SRD on every database invocation. We want to limit the number of hooks in the application and avoid modifying the database API. The database service API shall remain equal so as the tenants' applications code. Shuttle shall be transparent to application developers.

Shuttle architecture establishes that every database operation must include the SRD. The first solution would implement directly the architecture in Figure 3.2, in which a proxy that modifies every database request or modify the database client API to include the SRD as an argument. However, for

the sake of simplicity, we modified the Voldemort client to include the SRD field on every database operation. We modified the Voldemort messages, which are described using *Google Protocol Buffers* (protobuf) IDL (Appendix A.1). The implemented *interceptor* gets the SRD, which is written in request header, tracks the access and invokes the modified Voldemort client (Algorithm 2).

Algorithm 2: Voldemort API interceptor (example of put operation)

```
1 Function put(key, value, store)
2     srd ← trackKeyAccess (key, store, "put")          // get SRD and track
      access(Algo.4)
3     voldemort.put(key, value, srd)
```

In order to extract the SRD from the requests' header, we took in account that PaaS systems deploy applications in application engines. Specifically, AppScale deploys the Java applications on the servlet engine WildFly [86] (formerly known as JBoss). In addition, most of Web Service frameworks, e.g., *Java API for XML Web Services* (JAX-WS), and *Model View Controller* (MVC) frameworks, such as Spring, encompass the concept of interceptor chain, also known as filters or handlers. An interceptor chain is a sequence of handlers that contain methods that are invoked before and after the request processing by the application controller.

We implemented a *request interceptor* in Spring. Application developers only need to add a single line to their applications *web.xml* file to add the developed interceptor to the interceptor chain. A future work may concern the implementation interceptor for other application engines.

We also took into account that each request in Spring is binded to a single thread. Therefore, Shuttle keeps an hash table that associates the *Thread Id* (TID) with the SRD and list of accessed keys of the request that it is processing. The *request interceptor* parses the request header and creates an entry in the hash table (Algorithm 3).

Algorithm 3: Shuttle interceptor: Pre handler

Data: map is a static hash table
Input: HTTP user request

```
1 Function preHandle(request)
2     keySet ← new empty list
3     srd ← parse request header
4     tid ← get current thread id
5     entry ← create entry pair: {keySet, srd}
6     map.put(tid, entry)
```

Before every database operation, the database client library invokes the client interceptor to log the access. The interceptor resolves the TID into the request's SRD, adds the new key to the set of accessed keys of the SRD and returns the SRD (Algorithm 4). The client library appends the SRD in the database operation request.

The post-process interceptor (Algorithm 5) accesses the map extracting the accessed keys and the SRD of the current thread. The accessed keys are stored among the HTTP request/response in the Shuttle storage. In addition, this interceptor also adds the SRD to the response header.

Algorithm 4: Shuttle interceptor

```
1 Function trackKeyAccess(key, store name, operation type)
2     tid ← get current thread id
3     entry ← map.get(tid)
4     entry.addKeyAccess(key,store name, operation type)
5     return entry.srd
```

Algorithm 5: Shuttle interceptor: After completion handler

Data: map is a static hash table
Input: HTTP user request and HTTP response

```
1 Function afterCompletion(request, response)
2     entry ← map.remove(tid)
      // add accessed keys of entry to Shuttle Storage
3     shuttleStorage.add (srd, accessedKeys)
4     add srd to response header
```

4.2.3 Database

The Shuttle database proxy records database operations, selects the correct data item version to access according to the Shuttle state and performs snapshots. The proxy can be implemented in the database management system or as an external TCP proxy that accesses the requests. In this work, we implemented the proxy as a new library in the database management system. The database management system invokes the library before the execution of every database request. The proxy tracks the operations order to each data item recording an ordered list of the RID that accessed the data item. The operation sequence of each data item is sent to the *manager* to generate the dependency graph (Chapter 4.2.4).

We assume without loss of generality that applications store their state in distributed key-value stores, such as Dynamo [58], where the values are often accessed using a CRUD API. The simple API reduces the performance overhead to track accesses while the independence between keys turns Shuttle into a scalable service. Shuttle can be extended to support other NoSQL schemes, for instance column-oriented storage like Cassandra [85].

Voldemort is a distributed database store implemented in Java. We choose in-memory and *Berkeley DB* (BDB) as storage engines and Protocol Buffers as serialization and message passing protocol. Voldemort provides a CRUD API with 3 methods: get, put and delete. Voldemort accepts asynchronous concurrent writes and treats the result of each modification as a new and immutable version of the data. It detects version conflicts at read-time and handles them using vector clocks or semantic reconciliation. In this implementation, we assume the replication mechanisms to be disabled.

In the previous section (Section 4.2.2), we introduced the modified version of the Voldemort client library, which encompasses the Shuttle interceptor. The interceptor adds the requests' SRD to every database operation. We modified the format of the Voldemort messages, which are described using protobuf IDL, to encompass the SRD (Appendix A.1). This technique makes Shuttle transparent for

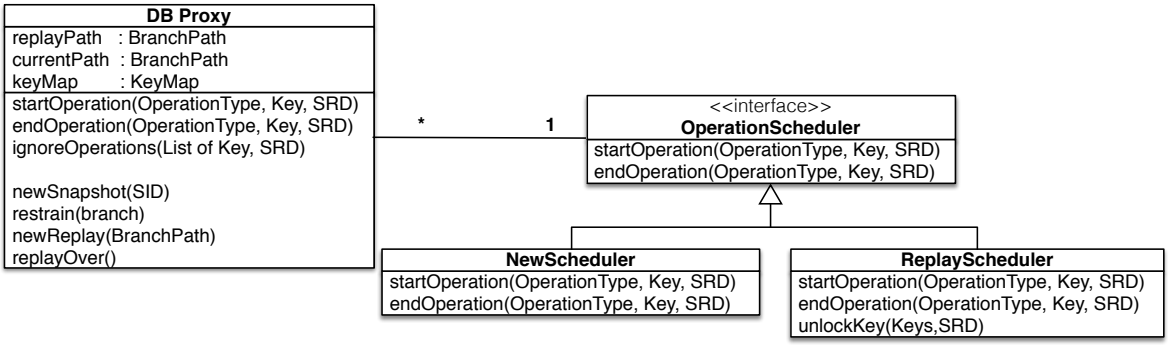


Figure 4.3: UML of Database proxy and schedulers

application developers.

The Voldemort implementation has been modified to invoke the Shuttle database proxy on every API call. The proxy architecture is based on the strategy design pattern: two operation schedulers decide how the operations shall be processed. The first scheduler, named *newScheduler*, is used by operations of new incoming requests. The second, named *replayScheduler* and described in Section 4.3.3, is used by operations of requests being replayed (Figure 4.3). Schedulers control the access to data items ordering the operations execution and selecting the correct version of data item to access, i.e., the snapshot and branch of the data item to be read/written by the operation. Voldemort is a key-value store, i.e., each data item is identified by an unique key. We implement the versioned storage concatenating the key with the version's snapshot (a version/snapshot can only be written in one branch).

Each database proxy maintains two *branch path*. A branch path of a certain branch is the sequence of non-tampered snapshots between the current snapshot and the root snapshot (Chapter 3.5.6). The first branch path, named *current branch*, refers to the branch used by new incoming requests, while the second, named *replay branch*, wraps the branch used by the requests being replayed.

Before each replay process, the Shuttle manager sends the branch path of the new replay branch, in which the requests will be replayed. At the end of replay process, the database nodes are also notified and the *replay branch* becomes the *current branch*. If the branch of the request is the *replay branch*, then it is being replayed. Otherwise, it is a new request.

First, we consider operations of new incoming requests. Shuttle tracks operations of new requests and allows a single write or multiple read operations per key. To do so, the Shuttle interceptor invokes the *newScheduler*, which invokes the *keyMap* (Figure 4.4). The *keyMap*, which is the main data structure of database proxy, is a concurrent hash table that binds each key to its Shuttle metadata, named *keyMapEntry*. To improve Shuttle's performance, the *keyMap* is internally partitioned to permit concurrent reads and updates.

Each *keyMapEntry* object wraps the Shuttle metadata for one key/data-item: *version list*, *operation*

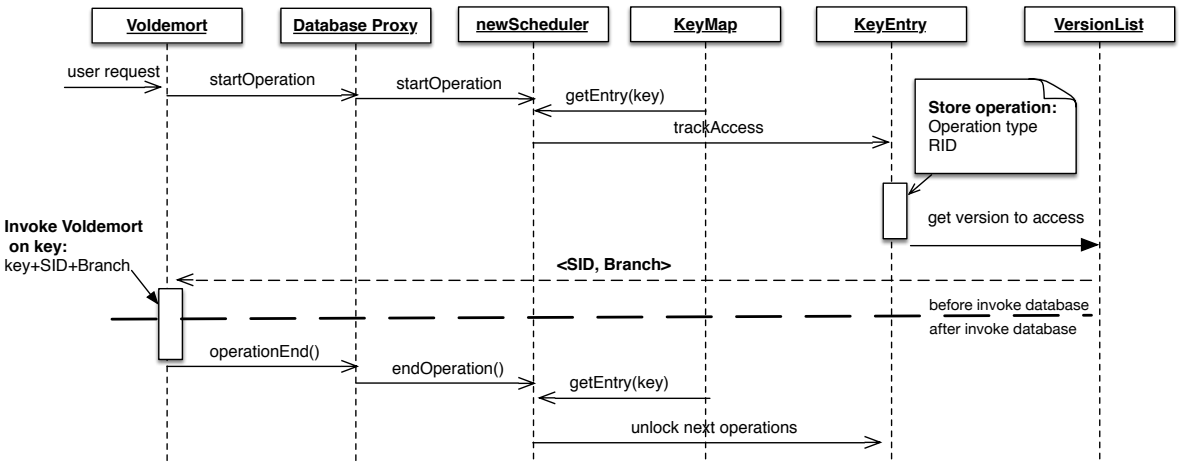


Figure 4.4: Sequence of invocations between the main data structures of database proxy

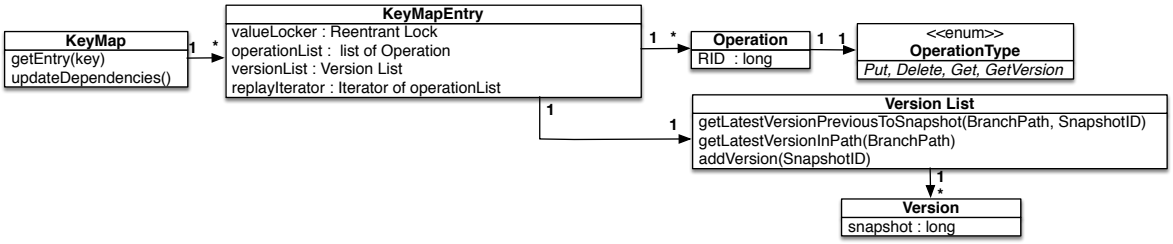


Figure 4.5: KeyMap UML: the entities used to to track operations and versions of each key.

list and *read-write lock* (Figure 4.5). The *version list* contains the list of versions: snapshot in which the entry has been written. A data item may not be written in every snapshot (Section 3.5.6).

The *operation list* contains the sequence of operations of a certain key (data item). Each operation has an operationType (put, get, delete, get version) and the RID of the retrieved requests. The *read-write lock* lock serializes the operation that access the key value allowing concurrent reads or a single write at each time. This pessimistic concurrency control method may decrease the system performance comparing, for instance, with a multi-version concurrency control. An alternative implementation can write the RID among the value in the store and track only the read accesses, parsing the accessed RID. The client library may parse the value to get the RID but the write order is relevant. For sake of simplicity, we used a pessimistic concurrency control with a reentrant mutual exclusion lock.

When *newScheduler* is invoked by an operation from a new incoming request, it gets the *keyMapEntry* of the key and attempts to gain the access to its *read-write lock* (Algorithm 6). Then, it adds the operation to the *operation list*. At last, Shuttle gets the correct version to access based on the *branch path* and the *list of versions* of the key (Section 3.5.6).

If the request RID is smaller than the current SID (line 7), then the request does not belong to the current snapshot and shall access the latest, but previous to the snapshot instant, version of the value that is in the *current branch path*. Otherwise, the request belongs to the current snapshot. Read operations access the latest version (line 12) in the *current branch path*. A write request may create

a new version if the version has yet not been written in the current snapshot (RID is bigger than the SID of the latest version) (line 13). Versions are created with the current SID. The key accessed by the request is the concatenation of the original key with the version returned by the Algorithm 6. After the access, the *read-write lock* is unlocked and the next operations proceed.

Algorithm 6: Method to track a new request, get the version to access and perform snapshot

```
1  Function trackAccess(operation type, srd, branch path)
2      if type is put or delete then
3          lock.writeLock()
4      else
5          lock.readLock()
6      operationList.add(new Operation(type, srd.rid))
7      if srd.rid < branch path.sid then
           // Access only the versions of previous snapshots
8          return latest version in (versionlist ∩ branchpath : version < srd.rid)
9      else
           // Access the latest version
10         latest ← get latest version in (versionlist ∩ branchpath)
11         if type is get then
12             return latest
           // New version is created if the request belongs to a newer
               snapshot
13         if branch path.sid > latest.sid then
14             version ← new Version(branch path.sid)
15             versionList.add(version)
16             return version
```

Since the *version list* keeps a pointer to the latest version and the pointer is updated if wrong, the average complexity of the Algorithm 6 is $\mathcal{O}(1)$: get the latest version and check if it belongs to the branch path, which is a HashSet. If the branch path size becomes a considerable storage overhead, the branch paths and version lists can be implemented as a bitmaps.

Shuttle collects the dependencies between requests transversing the operation list of every *KeyMapEntry* in the *KeyMap*. Each *KeyMapEntry* keeps a pointer to the latest collected dependency in the operation list, so only new operations are transversed.

In order to determine the dependencies between requests, Shuttle firstly lookup for the write operation previous to the latest collected operation (Algorithm 7). Then, it iterates the operations following to the latest collected operation. If an operation of request A reads a data item written by an operation of request B, then A depends on B. Dependencies are logged on a hash table that associates the operation RID with the RIDs which it depends on. Every database node sends its

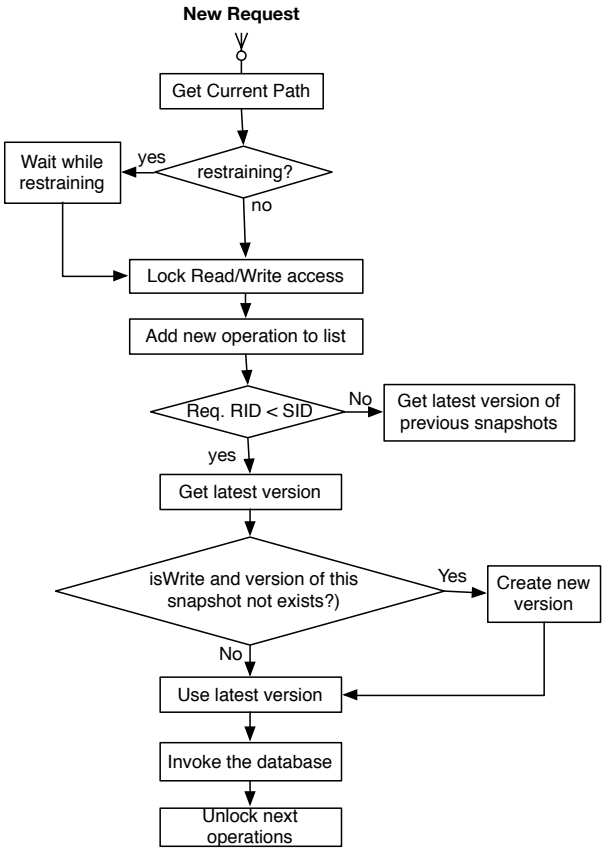


Figure 4.6: Diagram of processing a new database request

$dependenciesTable$s to the manager periodically.

Algorithm 7: Dependency collection

```
1  Initialization: dependencies ← new hash table<Long,Long>
2  foreach entry in keyMap do
3      lastWrite ← RID of the latest write operation previous to the earlier operation to collect
4      foreach operation in entry.operationList do
5          if operation.type == READ then
6              dependencies.add(operation.rid, lastWrite)
7          else
8              lastWrite ← operation.rid
9      entry.lastCollected ← latest operation in entry.operationList
10 send dependenciesMap to manager
```

NoSQL databases are designed for distributed environments. The proposed dependency tracking and snapshot mechanisms are horizontally scalable: each database node remains independent and each data item is independent from the others. The only locks shared by data items are the KeyMap partition lock and the KeyMapEntry lock. Adding more partitions, can improve the overall performance. Each node is responsible for logging local dependencies and communicates to a central entity (Manager) to update the dependency graph.

4.2.4 Manager

The main duties of manager are: retrieve dependencies between database operations and generate the dependency graph; coordinate database nodes to create new database snapshots; coordinate the recovery process.

In order to generate the dependency graph, dependencies are pushed to the manager by the database nodes. The dependency graph is updated during the normal execution. An alternative approach could pull the dependencies from each database node during the recovery phase and generate the graph during the recovery period.

The dependency graph is a set of vertexes, each one representing a request, and a collection of edges that each connect a pair of vertexes. Each edge specifies an one-way dependency between two requests. Therefore, the dependency graph is a directed graph. The dependency graph is also *not connected*, i.e., it consists of a set of connected subgraphs. Each vertex is uniquely identified by its key, the RID of the request that it represents.

The dependency graph has four main operations: insert new dependencies, get requests sorted by start instant, get requests dependent from a certain request, get requests from which a certain request depends on.

The first operation inserts new vertexes (requests) and adds edges between the new vertexes and all vertexes from which new vertexes depends on. The second visits every vertex by the order of their key (start instant). The two latest operations visit all vertexes reachable from a certain vertex using the *dependencies to* and the *dependencies from* directions, respectively. Even the dependency graph is, conceptually, a directed graph, the two latest operations are easier to implement on *undirected graphs*.

Two of the main representations of graphs in memory are: adjacent matrix and adjacent list. On a dependency graph, each insert operation requires to create several edges, one per dependency. An edge can be inserted on an adjacency matrix with complexity $\mathcal{O}(1)$. However, we consider the dependency graph to be a *sparse graph* because each request is expected to be dependent from a small part of all requests. Therefore, the adjacent list representation is expected to be more space efficient than the matrix.

The three main implementations of a adjacent list graph are: an indexed array, object oriented (nodes with pointers) and a hash table. The vertex keys are expected to be a sparse numeric sequence with irregular number of edges. Therefore an indexed array implementation would not be space efficient. Insert operations in object oriented graphs requires searching for objects to create new edges. However, a graph search algorithm, for instance breadth-first search (BFS), has a time complexity of $\mathcal{O}(|Vertix| + |Edges|)$ in the worst case. Hash table implementations use a hash table to associate each vertex in a graph with an array of adjacent vertexes. To clarify, each hash table object represents a vertex. The object has list of keys that represents the edges.

We implemented the dependency graph as a hash table. Doing so, insert operations have $\mathcal{O}(1)$ complexity. Operations to obtain the first level of dependencies of a certain requests has also have

Key	Value
RID: long	**end** : long **before** : list of RID **after** : list of RID

Figure 4.7: Entry of the dependency graph HashMap

$\mathcal{O}(1)$ complexity. Even so, we also take in consideration that the performance of these operations is influenced by constant factors and by the hashing function and data distribution.

The hash table keys are the RID, which is also the start timestamp of the request. The object associated with each key wraps: the end timestamp; the list of requests from which the request depends on (executed before); the list of requests dependent from the request (to execute after) (Figure 4.7). For sake of simplicity, the graph is kept in the memory of the manager. A production mode implementation, in which the memory limit can become a bottleneck, shall implement the dependency graph in a *Distributed Hashtable* (DHT) or a key-value NoSQL store.

The manager updates the dependency graph when a new table of dependencies is retrieved from a database node (Algorithm 8). The retrieved hash table associates each RID with the RID of the requests from which the request depends on. The algorithm creates an undirected graph, which can be considered as two directed graphs: the first representing the dependencies from; the seconds the dependencies two. In other words, the graphs are symmetric: one graph can be generated inverting the directions of the edges of the other graph.

Algorithm 8: Add dependency to dependency graph

Input: $dependencies \leftarrow$ HashTable<RID, list of RID>

1

2 **foreach** $\{rid, dependencyList\}$ *in* $dependencies$ **do**
3 $entry \leftarrow$ get or create a GraphEntry in dependency graph for rid
4 `entry.addBefore(`$dependencyList$`)`
5 **foreach** $dependentRID$ *in* $dependencyList$ **do**
6 $entry \leftarrow$ get or create a GraphEntry in dependency graph for $dependentRID$
7 `entry.addAfter(`*rid*`)`

The manager maintains the *BranchTree*. BranchTree is the implementation of the branching model introduced in Chapter 3.5.6. The BranchTree is implemented as a hash table that associates each branch and its snapshots. The tree model allows tenants to create new branches or snapshots.

In order to create a snapshot, tenants define a future instant in time, t, when the snapshot will occur. The manager forwards the value of t, named SID, to every database instance. Each database node adds a new snapshot with the retrieved SID in the *current branch path*. The manager insert the SID in the entry of the current branch in the *BranchTree*.

In order to create a new branch and start a new replay process, tenants shall specify a base snapshot. The branching algorithm finds the branch of the selected snapshot and copies the snapshots in the list, which are equal or previous to the selected snapshot, to create a new entry in the BranchTree for the new branch. Then, the algorithm creates a snapshot in the new branch. In other words, the new branch path is the concatenation of the new snapshot, in which the replay will be written, and the sequence of snapshots of the branch of the selected snapshots that are equal or previous to it.

The new branch path is send to the database proxy of all database nodes.

Shuttle's manager prototype retrieves tenant's commands via command line. Each module of Shuttle, including the manager, has a TCP server that retrieves requests from other modules. Requests are formatted using Google's Protocol Buffer [78]. Messages exchanged between the manager and the remaining modules are in Appendix A.2.

4.3 Recovery

In this section, we introduce the implementation of the recovery process in Shuttle.

The recovery process begins when the tenant selects a non-tampered snapshot. The manager creates a new branch and sends its *branch path* to all database proxies. The proxies set the new branch path as *replay branch* (Chapter 4.2.3). After, the manager generates the sequence of requests to replay, named *execution list*. The replay instances are launched and retrieve this list (Figure 4.8). Then, the replay instances are notified to start replaying the requests. After replaying all the requests, each replay instance notifies the manager. The manager sets the proxy state to *restraining mode* and commands the replay instances to replay the incoming requests retrieved during the recovery period. After replaying the remaining requests, the database nodes are notified to disable the restrain and *replay branch* becomes the *current branch*. At end, the proxy *restraining mode* is disabled and the following new requests are done in the new branch.

4.3.1 Manager

Tenants start the recovery process by selecting a snapshot that does not contain the result of any malicious action. Shuttle creates a new branch and sends its *branch path* every database proxy. After, the manager generates the request execution list, i.e., the sequence by the requests shall be replayed.

Shuttle can perform selective or full replay. It also can use clustering to re-execute different sequences of requests in parallel or not (Table 3.2).

Shuttle uses the Algorithm 9 to generate a request execution list for full-replay. The algorithm implements the start-end request ordering approach presented in Section 3.5.3. Since the graph is implemented as a hash table (Section 4.2.4), the keys are not ordered. At recovery time, the keys are ordered and the graph is iterated in order. The complexity of this operation is $\mathcal{O}(n \log n)$. A request must be executed concurrently with a previous request if it began before a previous request ends.

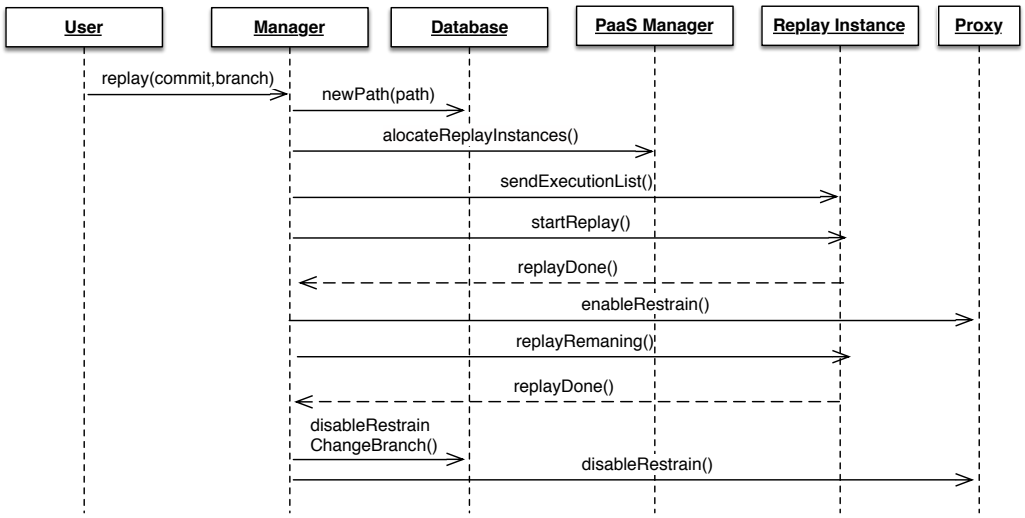


Figure 4.8: Message sequence during replay phase

Otherwise, the request was not executed concurrently with any of the previous requests.

Algorithm 9: Start-end ordering algorithm

Input: $graph$: dependency graph (Hash Table)
Input: $snapshot$: non-tampered SID selected by the tenant
Output: $executionList$: sorted list of RID to replay

```
1 Sort graph keys
2 latestExecuting ← -1            // the biggest end timestamp being executed
3 foreach request in graph do
4     if request.start => latestExecuting then
5         add separator to executionList /* none of following requests were
              executed concurrently with previous                          */
6     else
7         add request to executionList
8     latestExecuting ← max (latestExecuting,request.end)
```

The clustering mechanism identifies the connected subgraphs of the dependency graph. The algorithm traverses the vertex marking all adjacent nodes that are reachable from a node. The set of nodes reachable from a node defines a cluster. Then, we choose a non-marked node and repeat the procedure.

When the tenants provide a set of malicious actions, $A_{intrusion}$, Shuttle performs selective replay instead of replaying every request. Selective replay uses the dependencies between requests to expand a provided set of malicious requests, $A_{intrusion}$, to get which requests are needed to be replayed. The set of malicious requests is expanded adding all requests dependent from the initial malicious request set. The traversed nodes are the tainted requests, $A_{tainted}$. Then, the set $A_{tainted}$ is expanded transversing the nodes of the set on the opposite direction: visit requests from which the traversed node depends on and that are posterior to the selected snapshot (Figure 3.9).

The list of data items read by the requests in A_{replay} is obtained querying the Shuttle storage. The storage contains the keys accessed per request, which was logged by the application servers (Section 4.2.2). The snapshot versions of these items is loaded and the requests in A_{replay} are replayed. The

modified data items are merged with the current database values without copying data values. To do so, the *branch path* of a selective replay branch contains the current *branch path*. This mechanism avoids tainting the modified data items and copying them into the current database state. This mechanism does not support runtime recovery but the recovery period is considerably smaller than using full-replay.

4.3.2 Replay Instances

The Shuttle manager requires the PaaS controller to launch a set of *replay instances*. If the PaaS system does not support auto-scaling, the manager requests the PaaS controller to add new database and application instances to attend the flow of replayed requests. Otherwise, the auto-scaling mechanism will detect the overload of the application and database instances and trigger the creation of new instances. In the first case, the number of application instances is constant during the replay phase, so the instances send the requests directly to the application instance instances, avoiding the overhead of the load-balancer. In the second case, the requests are sent to the load-balancer that distributes the requests through the instances. In the current implementation, requests are sent to the load-balancer because AppScale supports auto-scalling and the number of instances during the replay phase is unknown.

Each replay instance retrieves a set of lists of RID to execute and the branch in which they shall be executed. Replay instances have a main thread to schedule the execution and a thread pool to execute requests asynchronously. Each thread fetches the HTTP requests from the *Shuttle storage*, modifies their header setting the SRD field *branch* and sends them to the load-balancer. Each response is compared against the response during first execution. An alternative approach can compute the hash of responses in background and compare their values.

If a request has been removed, for instance if it is a malicious request, the replay instance fetches the keys accessed by the malicious request during its first execution and invokes the database proxy to unlock the execution.

The prior evaluation, on serial-replay schema, showed fetching each request before sending is a considerable overhead. We duplicated the throughput and reduced the Shuttle storage usage by using a thread in background to fetch batches of requests from the Shuttle storage. The fetching thread and the execution threads communicate through a in-memory message queue.

The start-end algorithm (Algorithm 9) groups the requests that shall be executed concurrently. The separator marks the end of a group of concurrent request. When a separator is reached in the request list, the execution thread waits until all responses are retrieved. Even so, the number of concurrent requests within a group can overload the servers and database instances. In addition, since application server and replay instances are supported by thread pools, the system reaches a *deadlock* if all threads of one of the thread pools are blocked waiting for further requests. Taking that in consideration, all components in Shuttle shall be asynchronous and message-driven.

As requests are replayed asynchronous, the replay instances must use an end-to-end flow control protocol to avoid the sender send requests too fast for the application servers to receive and process. We implemented a simple flow control protocol, which does not have to lead with message ordering and retransmission because the underlying TCP protocol handles transmission failures. We established two thresholds for the number of pendent responses that define 3 deltas on the request rates. Consequently, the request throughput of each replay instance is dynamic to avoid the servers overload. One of main challenges to evaluate the Shuttle's prototype is to tune the threshold parameters. Future implementations shall access the PaaS controller in order to watch the instances' metrics and do flow control based on it.

4.3.3 Database

In Section 4.2.3, we introduced the *newScheduler* of the Shuttle's database proxy. Schedulers intercept requests and define their execution order. The *newScheduler* defines the order and logs the new operations. In this section, we introduce the *replayScheduler*. This scheduler constrains the replayed operations, per data item, to an order consistent with the original execution of the application.

Database operations are processed by the replayScheduler if the *branch* field of the operation SRD is the same than *replayBranch*. The replaySchedule gets the KeyMapEntry of the accessed key, which contains the list of operations logged during the execution phase. When the first operation, which is being replayed in current replay branch, accesses the data item, Shuttle creates an operation list iterator and associates it with the key.

The iterator of each operation list controls the replay process: it allows or blocks operations (Algorithm 10). The iterator keeps a list of operations allowed, executing, waiting or to be ignored. The first allowed operation is the first operation after the snapshot selected by the tenant, i.e., the smallest RID that matches the condition RID $>= snapshot$ (line 30).

When a new operation is retrieved, the iterator checks if there are operations executing or allowed to execute. If not, then the iterator transverses more operations of the list and adds them to the *allowed list* (line 9). The algorithm fetches the following consecutive read operations or one write operation. Operations previous to the selected snapshot are not considered.

If an operation is not the following operation, i.e., operation $\notin$ allowed, then the operation is delayed and added to the *waiting* list (line 16). Otherwise, the operation is allowed to proceed and is added to the *executing* list.

After its execution, the operation is removed from the *executing* list and blocked operations (in *waiting list*) are unlocked to check if they can access. For sake of simplicity, the concurrency control is not included in the pseudo-code.

Algorithm 10: Access iterator algorithm

```
1  Initialization:
2        all: list of all operations
3        allowed: list of operations allowed to execute
4        executing: list of operations executing
5        waiting: list of operations waiting to execute
6        ignoring: set of operations to ignore
7        nextOperation ← first operation after the snapshot

8  Function startReplayOperation(operation)
9     if allowed is empty and executing is empty then
10       fetchMoreAllowedOperations()
11    if operation in allowed then
          // move from allowed list to executing
12       allowed.remove(operation)
13       executing.add(operation)
14    else
15       waiting.add(operation)
16       thread sleep                                  // block operation
17       waiting.remove(operation)
          // Attempt to execute
18       startReplayOperation(operation)

19 Function fetchMoreAllowedOperations()
20    if nextOperation is write then
21       allowed.add(nextOperation)
22       nextOperation ← iteratorNext(nextOperation)
23    else
          /* add all read operations until next write                    */
24       while nextOperation is not write do
25          allowed.add(nextOperation)
26          nextOperation ← iteratorNext(nextOperation)

27 Function iteratorNext(operation)
      /* get next operation bigger than the base snapshot and not
          ignored                                                        */
28    do
29       operation ← operation.next
30    while operation.rid < SID or operation.rid ∈ ignoring
31    return operation

32 Function endReplayOperation(op)
33    executing.remove(op)
34    foreach operation in waiting do
35       wake operation thread
```

The iterator ignores operations that belong to previous snapshot (line 30), i.e., $operation.rid < snapshot$, or to the *ignoring* list. The *ignoring* list contains the operations that will not be executed. If a request is malicious, the replay instances invoke the database API method: $ignoreOperation(\text{RID}, keys)$ to ignore operations in all keys accessed by the request. In addition, when application servers retrieve requests and their replay flag is set, at the end of the request re-execution, the post-process interceptor of the database client library fetches the keys accessed by the requests during their first execution (Chapter 4.2.2). The process compares the keys accessed during the replay phase against the ones accessed during the first execution. The database client library invokes the method

$ignoreOperation(\text{RID}, keys)$ to ignore the database operations that the request did not perform during the replay phase. This mechanism allows the blocked operations to proceed.

Shuttle supports runtime recovery, i.e., the application remains online during the recovery process (Section 3.5.6). The field *branch* contained in every request allows the database proxy to separate the operations of new incoming requests from the operations of requests being replayed. The first use the *current branch* while the later use the *replay branch*. As introduced above, the *branch paths* and the scheduler algorithms define the versions which these operations read/write. This allows the new incoming requests to proceed during the recovery process.

At the end of the recovery process, the incoming requests must be switched to the application with fixed state, i.e., the requests should access the data items versions of the *replay branch*. When all requests are replayed, the manager interact with the proxy to set the SRD subfield *restrain* in every following incoming request. The *newScheduler* blocks the execution of new operations that have the *restrain* flat set. Requests performed after the beginning of the replay process are replayed. After, the manager broadcasts a message to every database node to set the *replay branch* as *current branch* and ignore the restrain flag. The proxy is notified to stop setting the restrain flag. Consequently, the blocked requests and further new incoming requests are processed. This mechanism causes a delay on the request process in exchange for a simplicity and low communication overhead.

4.4 Application Example: Ask

We considered several application types to evaluate Shuttle. The selected application shall represent a generic web application, retrieve HTTP requests and be deployable on AppScale. It should also fit the NoSQL key-value store model and store its state in Shuttle version of Voldemort [83]. The selected application should imply dependencies between requests but unlike some web applications shall not imply external consistence issues. Accordingly, the application shall read only static data from other services, except the database.

We consider real-world applications such as office productivity, gaming, media content, data aggregation, wikis, diagramming and e-commerce applications (with shopping cart). For sake of simplicity, we developed *Ask* instead of using real-world applications (Section 4.4). Even *Ask* implementation is based on the real-world application StackExchange, its implementation is simpler than it. This allows to analyze the dependencies and reason about the results. We expect to evaluate the dependencies created by different types of application in future.

We developed a *Questions and Answers* (Q&A) web application, named *Ask*, to evaluate Shuttle prototype. *Ask* is based on Stack Exchange [87] and Yahoo! Answers [88]. The application data structure is as follows (Figure 4.9). A question has a title, a known number of views by clients, a set of tags, which represent the themes of the question, and a set of answers. Each answer has a text and a number of user votes. Each user can only do a single vote per answer, incrementing or decrementing one unit the number of votes. Each answer has a set of comments.

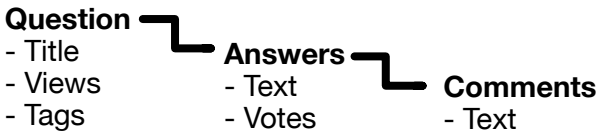


Figure 4.9: Data structure

	Read	Write	Depend on
New Question	(Tags)	(Tags) Question	(Tags)
New Answer	Question	Question, Answer	Previous answer to the same question
New Comment	Answer	Answer, Comment	Commented answer
New Vote	Answer	Answer, Vote	Voted answer

Table 4.2: Dependency list

The data is stored in four Voldemort stores (database schemas): questions, answers, comments and tags. For example, insert a new answer requires to add an entry to the *answers store* and modify the entry of the corresponding question in *questions store* to update the answer list.

Independent user sessions would be trivial to replay in parallel. Therefore, the application semantics implies the following dependencies: a) questions are independent; b) a new answer depends on previous answers and votes to the same question; c) a new comment depends on the commented answer; d) a new vote depends on the voted answer (Table 4.2). In Chapter 5.2, we compare the number of clusters considering or not dependencies between questions with the same tag.

Figure 4.10 represents an example of the application dependencies graph generated by Shuttle when two questions, two answers and one comment are created. Questions are independent, since they do not share a tag. Dashed entries represent read-only requests without consequent writes. A future work may consider to ignore these requests.

The application is implemented using Java Spring [89], which is one of the most used Java enterprise web systems and it is compatible with most of the current PaaS systems (Section 4.1). The implementation is independent of Shuttle. Shuttle does not require the application to be modified, except adding the Spring interceptor (Section 4.2.2).

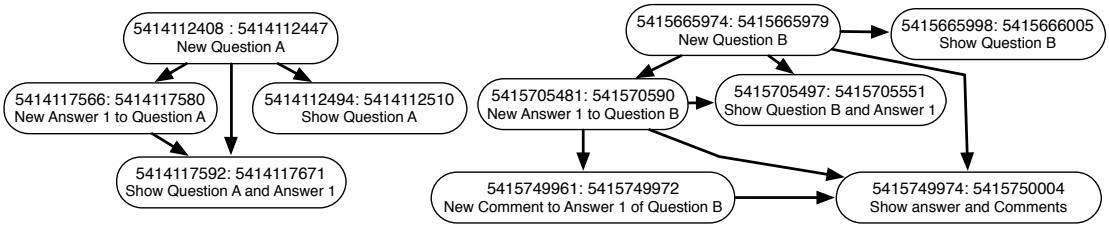


Figure 4.10: Example of a dependency graph generated by Shuttle

4.5 Chapter Summary

We presented the main implementation details of Shuttle prototype in Java. The total number of lines of code, except the unit tests, is summarized in Table 4.3.

The main development challenge is to implement 8 separate modules: TryOut master/slave, Proxy, Manager, Replay master/slave, database client interceptor, database proxy. In addition, the performance of each module is critical to demonstrate that this approach is valid. Therefore, each module is multi-thread and requires implementation of concurrency control. At least, the large data set implies issues with memory allocation.

Components	**Lines of code**
Proxy	1400
Voldemort	1800
Manager	100
Replay	900
Database Client Interceptor	300
TryOut	3000
Ask	1700
Total	**11 000**

Table 4.3: Components of Shuttle prototype and an estimate of their complexity, in terms of lines of code

5

Evaluation

In order to evaluate the developed solution, we performed several tests to measure the accuracy and performance of Shuttle. Due to public cloud costs, we performed an accuracy test prototype on a single machine and evaluate the prototype performance on a public CSP.

The following sections detail the steps and decisions towards evaluating the proposed solution, starting by the definition of the developed prototype application and performed tests. The recovery accuracy and performance are evaluated on a set of intrusion scenarios. Finally, we present a cost estimation for Shuttle in AWS [65]. The success of Shuttle is determined by its capability to recover from the intrusion scenarios in a correct, timely and scalable way.

5.1 Tests Description

We developed a HTTP load testing and benchmarking tool, named *TryOut*, to evaluate Shuttle and measure its overhead simulating a real application load from multiple clients. *TryOut* consists on multiple HTTP clients, which are deployed in various nodes, coordinated by a master node. It measures the average, minimum and maximum response time, the request rate and the throughput of each HTTP client. *TryOut* also compares the database entries and the user responses with the expected values to measure the precision and recall of our solution. TryOut allows to measure the latency for a given throughput and number of concurrent clients. Requests can be issued asynchronously or synchronously. It also allows to measure the maximum throughput supported by the service. Its main feature, comparing with tools such as Jmeter [90], ab [91] and weighttp [92] is the capability to perform HTTP requests based on data contained in files. This feature allows us to easily test Shuttle with a data set extracted from an application in production.

In order to use real-world data, *TryOut* performs requests to the developed Q&A application (Chap-

ter 4.4) with data extracted from the *Stack Exchange Data Dump* [93]. StackExchange, which is one of the largest Q&A applications and includes *StackOverflow.com* [94], is ranked 57th for traffic in the world [95]. A 24 hours window has: 36 million page loads, 148 million HTTP requests (1712 requests per second), 267GB retrieved, 1TB sent, 334 million SQL queries [96]. A question takes, in average, 28ms to be rendered. The architecture encompasses 1 load balancer, 2 SQL servers, a Redis [97] (a key-value cache and store) server and 3 web servers. Their architecture scales vertically, for instance the SQL servers have 384 GB of memory with 1.8TB of SSD storage. Since 98,82% of the requests are read requests, the StackExchange infrastructure relies on caching.

StackExchange provides a SQL database dump of each portal of StackExchange. We processed all dump files, a total of 60GB of text files, using MapReduce [98] to extracted the questions, answers, comments and votes. We used four MapReduce jobs to process the data: group comments per answer; group answers per question; output grouped by question; output grouped sorted by time. Doing so, we obtained two files: one grouped by question, the other sorted by they. Tables 5.1 and 5.2 describe the collected data. The original data was created between 1 August 2008 and 4 May 2014 (181565797230 milliseconds or 2102 days).

	Total
Questions	8 860 649
Answers	15 475 157
Comments	36 486 605
Votes	70 898 355
Tags	74 205
Views	11 097 152 219
Text of questions and answers (UTF-8)	26.76 GB
Text of comments (UTF-8)	5.61 GB

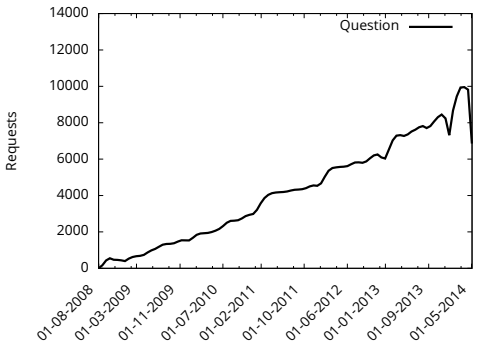
Table 5.1: Data description

	Average	**Std. Deviation**
Views per question	1252	6216
Tags per question	1	1.41
Answers per question	1	1.73
Comments per answer	2	3.16
Votes per answer	4	17.11
Text per answer (UTF-8)	883 B	1133.9 B
Text per comment (UTF-8)	153 B	122.5 B
Text per question (UTF-8)	1477 B	1951.1 B

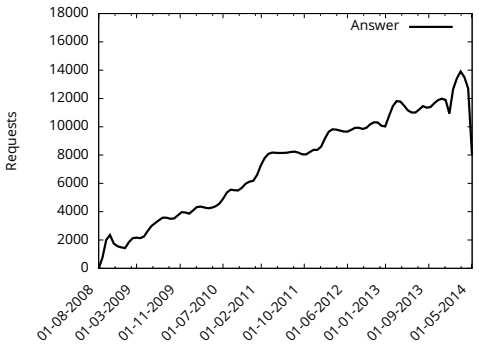
Table 5.2: Data description per question

The Figure 5.1 shows the number of new questions, answers and comments per day in the collected data during sampling period. Considering the collected data, we can set a supreme limit of 182 000 *write requests* per day (2 per second if we consider a constant request rate).

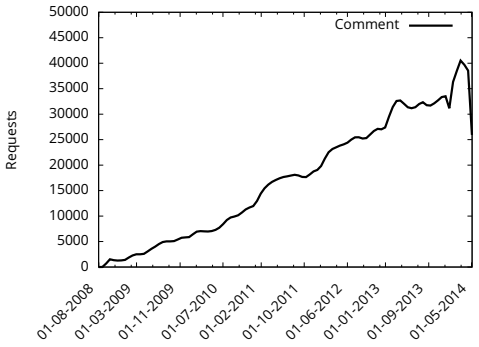
In order to set the throughput expectation for Shuttle, we assume the following request rate ranges for each category of application (Table 5.3). We consider small-scale applications to retrieve less than 5 million requests per day, enterprise scale retrieve between 5 and 100 million and web scale process from 100 million to billions of requests per day. For instance, the maximum request arrival rate of one of the Portuguese Ministry of Finances web applications in 2013 was 836 requests per second and 16 million requests in total [99]. In contrast, the total number of requests per day of StackExchange is 148 million (1712 requests per second). We aim that Shuttle fits on current requirements for small and enterprise services.



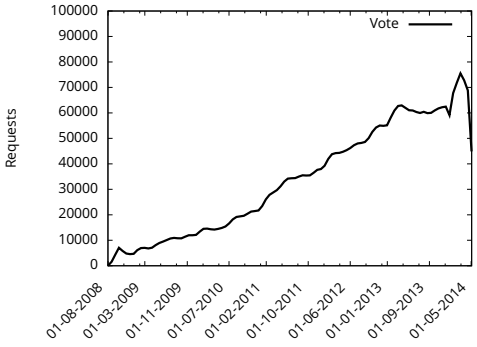
(a) Question requests



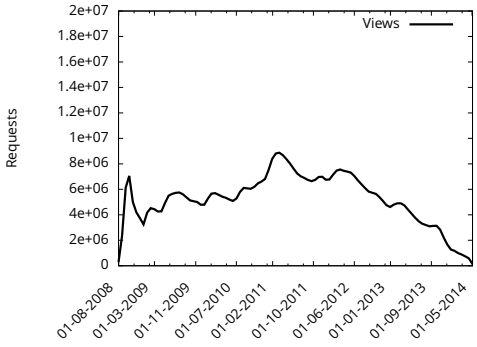
(b) Answer requests



(c) Comment requests



(d) Vote requests



(e) Question views

Figure 5.1: Number of requests per day

Category	Requests per day (Million)
Small	[0, 5[
Enterprise	[5,100[
Portuguese Ministry of Finances	16
Web scale	[100,+∞[
StackExchange	148

Table 5.3: Throughput per web application category

5.2 Precision and Recall

In this Section, we evaluate Shuttle's ability to correctly recover applications by measuring its precision and recall in three categories of intrusion scenarios. We define precision as the fraction of replayed requests that are legitimate and tainted requests:

$$precision = \frac{\{tainted \quad requests\} \cap \{replayed \quad requests\}}{\{replayed \quad requests\}}$$

We define recall as the fraction of legitimate and tainted requests that are replayed:

$$recall = \frac{\{tainted \quad requests\} \cap \{replayed \quad requests\}}{\{tainted \quad requests\}}$$

We also may defined precision and recall in terms of malicious and tainted requests.

We propose three intrusion scenarios encompass five of the *Open Web Application Security Project* (OWASP) Top 10 Application Security Risks: injection flaws, broken authentication, security misconfiguration, missing function level access control and using components with vulnerabilities [16]. We consider three classes of intrusion scenarios:

- Malicious requests that accidentally or maliciously compromise the application
- Software vulnerabilities
- External channels (e.g. *Secure Shell* (SSH) connections)

We deployed all Shuttle modules, application instance and database on a single node, a 2.9GHz dual-core Intel i7 with 8GB of memory running the Java 1.7 HotSpot VM. This configuration handled, on average, 500 requests per second from a single-thread client. We selected a subset of the *StackExchange Data Dump* [93] containing 100 000 requests originally performed from 31 of July until 12 of September of 2008: 6992 questions, 28 993 questions, 2200 comments, 61 795 votes . Requests were sorted per date, establishing 92 939 dependencies. For the sake of simplicity, we ignored view-only requests because the responses to every write requests imply to read the modified question.

We considered that intrusions happen at 2nd of September, when the database contains 4338 questions, 18286 answers, 422 comments and 38334 votes (61380 requests). The attack is detected in Sep. 12th, assuming a pessimistic delay of 10 days. During this period, the application retrieved 38 620 requests.

Table 5.4 presents a summary of the precision and recall tests. It contains the number of data items tampered by the intrusion (*#intrusion*) and the number of user requests that read data items written by tainted requests or malicious requests (without considering the intrusion requests). Recovery using *full replay* requires to replay every request from the latest snapshot before the intrusion instant until the detection instant: in this example at least 38 620 requests (*#replayed (fr)*). Selective

	#intrusion	#tainted	#replayed (sr)	#replayed (fr)
1a	110	0	[0, 605] (18.18%)	> 38 620 (00.28%)
1b	58	14	[0, 379] (18.99%)	> 38 620 (00.18%)
1c	48	52	[0, 253] (39.52%)	> 38 620 (00.25%)
2a	4 338	0	-	> 38 620 (11.23%)
2b	18 286	1 278	-	> 38 620 (50.67%)
3	2 000	-	-	> 38 620 (05.17%)

Table 5.4: Number of requests replayed during the recovery process and its precision within parenthesis.

replay only re-executes tainted requests, unless some data item versions need to be recreated. On the worst case, the system does not contain any snapshot and every data read by the tainted requests shall be recreated (*#replayed (sr)*). Since Shuttle removes all the malicious actions and recovers all the legitimate requests, it has 100% recall. The selective replay has better precision than full replay because it replays less non tainted requests.

5.2.1 Result consistency

Shuttle aims to support various PaaS applications. Unlike previous works that know the application semantics [31], the semantic of PaaS applications is unknown to Shuttle. In order to evaluate the consistency of the results, we need to define the results expected by tenants.

For instance, if an attacker created a new question and a legitimate user attempts to create a question with the same title. During the replay, the attacker action will be removed. Should the legitimate request be replayed and create the question? On one hand, the user may have created a question with another title but same content. On the other hand, the request contains the title that the user pretended and he may have not created another question.

Therefore, we argue that developers should consider the application recovery during the design of the application. For instance, if questions are identified by the hash of their text instead of their title, then the legitimate users create a new question only if the text is not equal to the one of other questions. Shuttle does not replay actions which fail during their first execution. In summary, despite Shuttle's consistency API (Section 3.5.7), developers shall take into consideration the replay process in order to obtain the expected results.

Considering the semantics of our Q&A prototype, we identify the expected results on the following most likely attack actions:

1. **Create new question:** The attacker created a new question with a specific title. The following legitimate user requests, which try to create a question with the same title, fail. When the attacker request is removed, the legitimate user requests will perform correctly and create the question. Answers to the removed question will be included in the new question.

2. **New answer:** The attacker answer is removed correctly. Since comments to a non-existing answer fail, the comments are also removed.

3. **New answer to every question:** Same behavior as to a new answer for a specific question.

4. **Modify the question:** The attacker can change the title or the text. The first case is similar to create a new answer. On the second case, Shuttle loads the previous text value.

5. **Modify the answer:** If the attacker changes the text, then Shuttle restores the previous text. However, the comments content may become inconsistent with the answer.

6. **Delete all questions or answers:** Shuttle restores the deleted data. However, the duplicated questions and answers will fail to create.

5.2.2 Malicious Requests

In the first class of scenarios, we consider three cases in which an attacker has stolen an user credential. The attacker uses the stolen credential to impersonate a legitimate user and to perform malicious actions. The method used to obtain the credential is out of the scope of this dissertation. This scenario is similar to a legitimated user who makes usage mistakes. We consider attackers:

a Deleted every question created by the user

b Deleted every user answer

c Modified every user answer

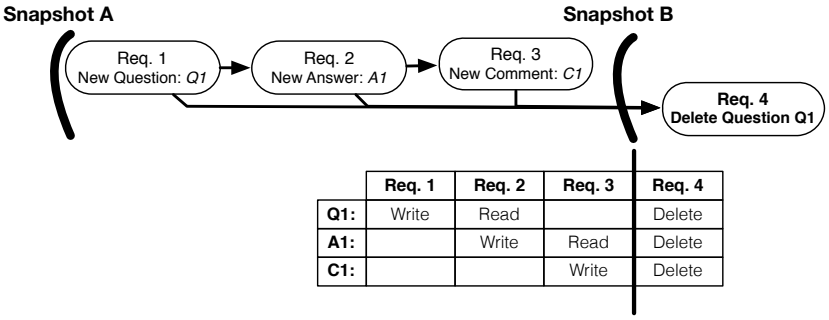
1a) The attacker deletes the user's 4 questions, performing 4 delete requests that remove 106 associated comments and answers. The tenant identifies the malicious requests through the user session and selects a snapshot previous to the intrusion instant. Users cannot access deleted questions, so no request is tainted. If Shuttle has a snapshot containing the deleted questions, then *selective replay* does not need to replay any request and merges the deleted questions on the current system state. If the latest snapshot is previous to the creation of the 4 questions, then *selective replay* replays 605 requests to recreate the deleted questions, their answers and votes. The result is merged with the current branch, rebuilding the deleted questions.

To clarify consider the Figure 5.2 in which the *Req. 4* deletes a question with one answer and one comment. *Req. 4* is a malicious request and the values written by it ($Q1, A1, C1$) need to be removed. If tenant selects the *snapshot B*, then the items $Q1, A1, C1$ are restored to the version before the delete operation and no operation is replayed. If the tenant selects the *snapshot A*, then *Req.1, Req.2, Req.3* are replayed to obtain the value of the $Q1, A1, C1$.

The following scenarios are similar.

1b) Deleting the user's 48 answers implies that 58 data items are deleted and 14 answers and comments are tainted as they execute after the intrusion instant answering and voting without knowing some answers. If a snapshot containing the user answers exists, then the *selective replay* approach replays only 14 tainted answers and comments. Otherwise, it replays 379 requests: the total number of requests to recreate the tainted questions and then merge the result.

1c) 48 data items are modified while 52 requests are tainted because the users replays, votes and comments the modified questions after the intrusion instant. For recovery, the 52 tainted requests



	Req. 1	Req. 2	Req. 3	Req. 4
Q1:	Write	Read		Delete
A1:		Write	Read	Delete
C1:			Write	Delete

Figure 5.2: Example of request dependencies: a malicious request deletes a question with one answer and one comment

shall be replayed. If Shuttle does not have a snapshot containing the questions, then 253 requests have to be replayed to recreate them.

5.2.3 Software Vulnerability

On the second class, we evaluate intrusion scenarios where software flaws allow attackers to modify the database without authorization. For instance, a code version added a flaw that allows *SQL-Injection*. We consider two independent scenarios where the attacker:

a Deleted every question

b Deleted every answer

In *2a)*, the deleting of every question removes 4 338 data items. In *2b)*, the questions are preserved but 1 278 answers, votes and comments are tainted as the user did not see the deleted answers.

Instead of identifying the requests that explored the vulnerability, the tenant patches the code to remove the application vulnerability. The instance rejuvenation mechanism terminates the current application instances and deploys the newest application version (Section 3.5.5). Then, they use the *full replay* to repeat all requests since the beginning of usage of the software version with the flaw. Requests that explored the vulnerability fail to execute and a consistent application state is recovered.

Shuttle can also be used to perform preventive updates. Consider the following case: the security team considered that: a) every answer shall be ciphered using the username; b) users without weak-passwords shall not be allowed to answer questions. The development team can rapidly develop a new software version fixing these vulnerabilities. Without Shuttle the system administrator would need to create a script to make the database consistent with the new software version. Shuttle can remove these steps, which require extensive human intervention, by replaying every user request.

5.2.4 External Channels

On the third class of intrusion scenarios, we consider a case where the proxy does not log the attacker actions. In this section, we propose how to recover from a shellshock attack using Shuttle.

Shellsock vulnerability allows an attacker to execute commands that are interpreted by the bash, i.e., perform code injection. When an attacker sends a HTTP request containing the header *User-Agent: () { :; }; <malicious command>* and the web server passes this header field as a bash variable, the bash interprets the malicious command. For sake of clarity, we omit further details. In summary, this vulnerability allows a HTTP request to run bash commands.

We consider a case in which an attacker used an HTTP request to create a new SSH user account in one application server. Then, the attacker established a SSH connection to an application server using the new user. The attacker stolen a database credentials stored in the application code. The attacker used the credentials to modify at least 2000 data items bypassing Shuttle's database proxy. As consequence, the database operations are not logged and the number of tainted requests is unknown.

Tenants can use Shuttle as a request logger to detect the string that exploits the shellshock vulnerability: *() {:;};*. If an intrusion is detected, the tenant selects a snapshot previous to the request creation, which does not contain data tampered by the intrusion. Since the application instances can be tampered, Shuttle uses the instance rejuvenation mechanism to terminate these instances and redeploy the application in new instances, in which the shellshock vulnerability is fixed.

Shuttle removes the attack effects and recovers the application consistency performing *full replay*. It loads a full database snapshot instead of undoing operations. As consequence, even non-logged operations are undo. Then it replays every HTTP request posterior to the snapshot instant. Since malicious actions were not logged, they are not replayed.

The described scenario assumes that Shuttle's trusted computing base is not compromised.

5.2.5 Discussion

The number of requests to replay is defined by the snapshot instant: on *full replay* Shuttle replays all requests performed after the intrusion instant, while on *selective replay* Shuttle replays the requests necessary to read the values of the entries before the intrusion and the tainted requests. While *selective replay* seems to have a big advantage comparing with *full replay*, which performs, in these scenarios, at least 38 620 requests, most real applications have more dependencies thus the number of tainted requests is bigger. For instance, if the order between questions with the same tag is considered as a dependency, the number of dependencies rises from 92 939 to 109 118 and the number of independent clusters decreases from 6992 to 56. We plan to further analyze the dependencies established by different types of applications.

5.3 Overhead

The performance evaluation aims to prove Shuttle scalability and capability to support small and enterprise applications (Section 5.1). Its results should match the evaluation metrics bounds that allow to use Shuttle in real environments. We evaluate Shuttle's performance considering the through-

put of the application, the size of the logs and the recovery time. We also estimate the cost of deployment of Shuttle on a public cloud provider (AWS [65]).

We run Shuttle in AWS. All instances are connected by gigabit ethernet (780Mbps measured with *iperf*, 0.176ms round-trip time measured with *ping*) and have the *Java 1.7 HotSpot* 64-Bit Server VM version installed. Even when the *Java Virtual Machine* (JVM) performance increases as the bytecode is compiled by the *Just-in-time* (JIT) compiler, we run every test on new JVM instances. They have a 32GB local general purpose *Solid State Disk* (SSD). We used the local SSD since its performance on read is better than a 500 Provisioned *Input/Output Operations Per Second* (IOPS) SSD of 25GB 5.5. We allocated 5GB of heap to the JVM and we disabled database replication (each data item is stored in one data node).

	putc()	**Block Write**	**Create,Change,Rewrite**	**getc()**	**Block Read**
EBS SSD	631	83264	44448	1562	105723
Local SSD	619	106546	186204	1577	614790

Table 5.5: Comparison between a EBS Provisioned IOPS (SSD), which supports up to 500 IOPS, and a local SSD instance using bonnie++ (KB/s)

5.3.1 Performance Overhead

In this section, we quantify the overhead imposed by each component of Shuttle.

5.3.1.1 Database

We measured the overhead of Shuttle on database instances. We expected it to be the major impact of Shuttle because Shuttle logs every operation. We used *Yahoo! Cloud Serving Benchmark* (YCSB) [100]. YCSB was developed to measure the performance of the new generation of cloud data serving systems, such as Voldemort used in Shuttle. We extended YCSB to support the latest version of Voldemort and to use protobuf as request format.

We used 6 *m3.large* instances (7 *EC2 Compute Unit* (ECU)s, 2 vCPUs, 2.8 GHz, Intel Xeon E5-2680v2, 3.75 GiB memory, 2 x 16 GiB Storage Capacity) to run each database node. The database service was accessed by two *c3.xlarge* instances (14 ECUs, 4 vCPUs, 2.8 GHz, Intel Xeon E5-2680v2, 7.5 GB of memory, 2 x 40 GB Storage Capacity).

We ran 4 out of 5 workloads (Table 5.6) proposed *in YCSB* [100]. Workload E (Short ranges) is not supported by Voldemort. Our database consisted of 60 million 1KB record (total database size: 60GB). Each instance thus had an average of 10GB of data, more than it could cache entirely in memory. Read operations retrieve entire records, while update operations modify one of the ten record fields [100]. YCSB selects the record to read or write with a Zipfian or latest distribution. On zipfian distribuition some records will be extremely popular (head of distribution) while most of records will be unpopular

(the tail). On latest distribution, the most recently inserted records are in the head of the zipfian distribution.

Workload	Operations	Record Selection	Application Example
A - Update heavy	Read: 50% Update: 50%	Zipfian	Session store recording recent actions
B - Read mostly	Read: 95% Update: 5%	Zipfian	Photo tagging; add a tag is an update, but most operations are to read tags
C - Read only	Read: 100%	Zipfian	User profile cache, where profiles are constructed elsewhere (e.g., Hadoop)
D - Read latest	Read: 95% Insert: 5%	Latest	User status updates; people want to read the latest

Table 5.6: Workload description

We expected the major Shuttle impact on database to be the read-write lock. Shuttle serializes the requests per-key using a read-write lock. In addition, the underlying BDB, which is used by Voldemort as persistent-storage, also uses a read-write lock. However, the results in Figure 5.3 prove that Shuttle imposes a negligible latency overhead for the various types of workload and request rate.

Shuttle also iterates over the *operation lists* to determine the dependencies and sends them to the *manager*. The instance's CPU usage was 10% in average and the throughput did not reveal any variation when the dependencies are being collected.

Shuttle snapshot mechanism requires creating a new data item in the Voldemort database and creating a new data version. A new version takes 264.077 μs (standard deviation 864.293 μs) to be created, while overwrite a version takes 266.635 μs (std. deviation 577.124 μs).

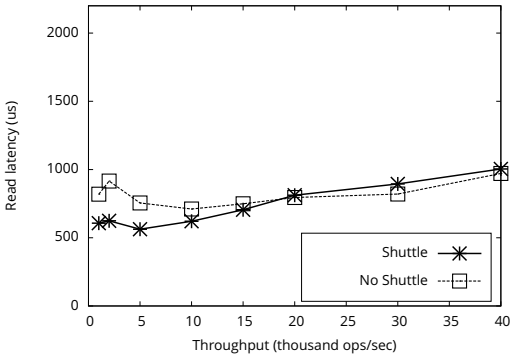
We conclude that Shuttle database proxy does not represent a significant performance overhead.

5.3.1.2 Proxy

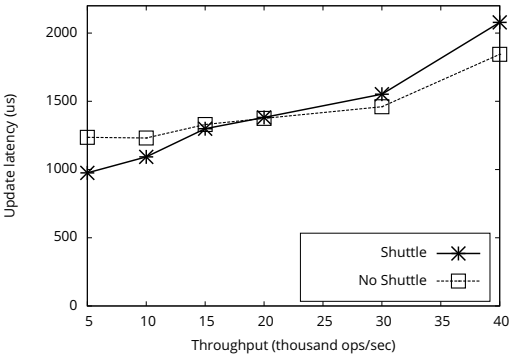
We setup an environment with 3 AWS *c3.xlarge* instances to measure the proxy overhead. The first runs a HTTP benchmark tool *weighttp* [92]. The second runs a HAProxy (v1.5.3) as load balancer and the Shuttle's proxy. The third runs a WildFly serving a 1KB static file. The benchmark tool performed 2 million requests using 8 threads and 200 clients.

Figure 5.4 represents the throughput limit imposed by Shuttle's proxy. Shuttle's proxy imposes a considerable performance limitation (c) comparing with the load balancer (b). On the contrary, the logging mechanism has a negligible influence on the maximum request throughput (column *d* comparing with column *e*). In addition, the table in Figure 5.4 shows that Shuttle imposes a negligible overhead on requests latency considering a constant request income rate of 2500 requests per second.

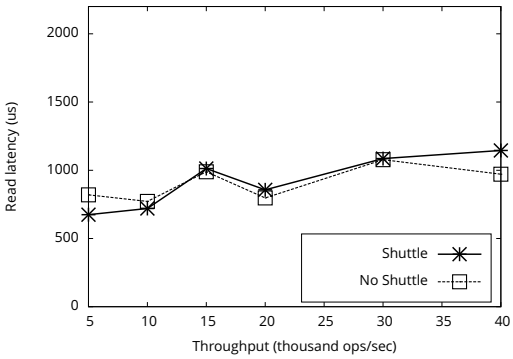
We conclude that the performance overhead due to logging is negligible but the proxy is a considerable throughput limitation. The main cause is its implementation: while HAProxy is implemented using C and it is heavily optimized, Shuttle's proxy is a prototype implemented in Java. Therefore, we expect a C implementation of proxy can overcome the performance overhead. However, we claim that our prototype implementation is enough for most of small and enterprise services deployed in



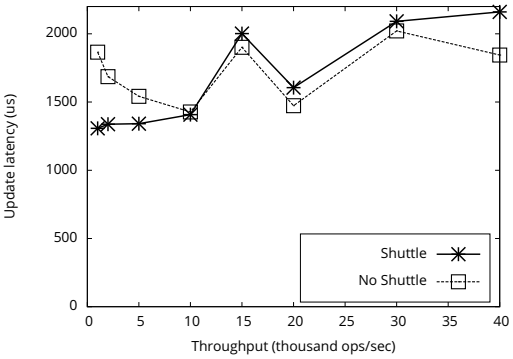
(a) Workload A: read operations



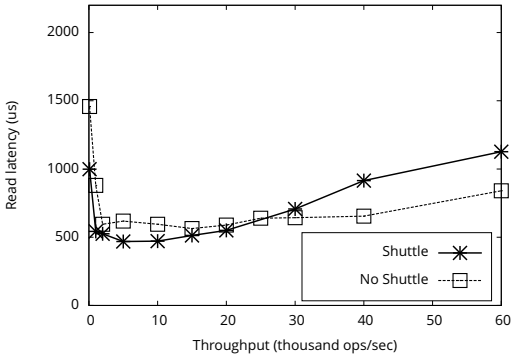
(b) Workload A: update operations



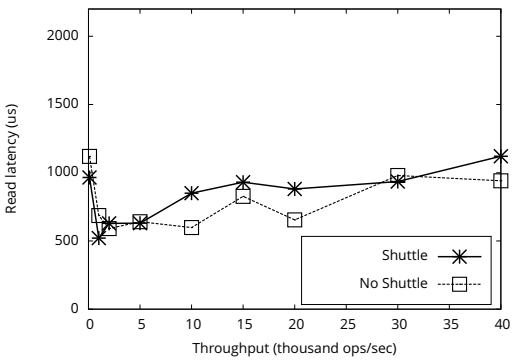
(c) Workload B: read operations



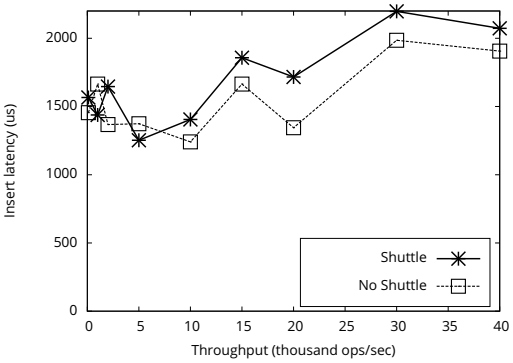
(d) Workload B: update operations



(e) Workload C: read operations

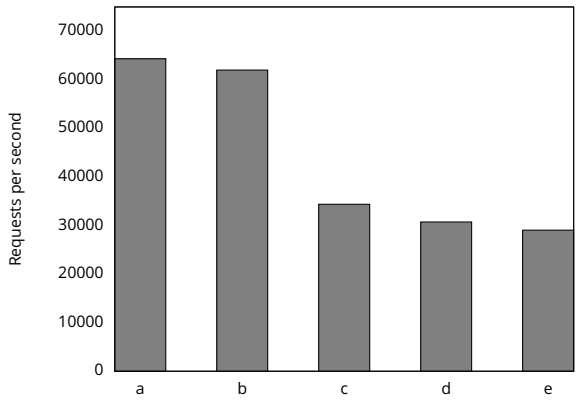


(f) Workload D: read operations



(g) Workload D: insert operations

Figure 5.3: Shuttle overhead on database



	Load Balancer	Proxy	Latency (ms)
a			1.08 (1.17)
b	✓		1.08 (1.25)
c		✓	1.11 (1.28)
d	✓	No log	1.10 (1.27)
e	✓	✓	1.11 (1.29)

Figure 5.4: Proxy Overhead: *a)* direct to the server; *b)* only with the load balancer (HAProxy); *c)* Shuttle logging but without load balancer; *d)* overhead of Shuttle with load balancer when not logging and logging. The table describes the scenarios of the graph and the request latency (average and 95th percentile) in them.

PaaS because the throughput limit imposed by the proxy is lower than the request rates presented in Table 5.3. Moreover, the recovery time is dependent from the application performance but independent from the proxy's performance.

The overhead of Shuttle on each application server is the database client interceptor that logs the accessed keys per request. Our experiments demonstrated that logging and storing the accessed keys implies a negligible overhead on the response latency.

5.3.1.3 General Overhead

The previous sections assessed the overhead in the database and of the proxy. In this Section, we assess the general overhead of Shuttle by measuring the throughput of the *Ask* application with and without Shuttle (Table 5.7). We do not consider a particular scenario or replay scheme (full/selective) but define instead the number of requests recovered per experiment. We run 6 AWS *c3.xlarge* instances. We use one client, one instance with Shuttle proxy and a load balancer (HAProxy), three WildFly application servers and one Voldemort database.

We considered two workloads: (A) has 50% reads, 50% inserts and (B) has 95% reads, 5% inserts. Insert operations adds questions, answers, comments and votes of the data sample, while read operations access the latest inserted questions. The insert operations insert the questions, answers, comments and votes of the data sample, while the read operations access the latest inserted questions. We consider a large data sample from *StackExchange Data Dump* [93] with 3 million requests (250812 questions, 335312 answers, 717937 comments, 1695939 votes).

Table 5.7 shows that Shuttle imposes an overhead of 13-20%, which seems reasonable considering the benefits of having it. We believe the main cause of overhead is the current proxy, which is not very optimized. The current version written in Java performs considerably better than a previous version in Python, but we expect to be able to do much better by rewriting it in C. Still, while the proxy and database instances consume a low level of resources, the application instances consumed the maximum of CPU resources available.

	Workload A	Workload B
Shuttle	6325 ops/sec [5.78 ms]	15346 ops/sec[3.62 ms]
No Shuttle	7148 ops/sec [5.07 ms]	17821 ops/sec[3.01 ms]

Table 5.7: Shuttle overhead in terms of application throughput (ops/sec) and response latency (ms)

Considering the request rates presented in Table 5.3, we claim that a small environment with 6 machines is enough to support a small to medium application running with Shuttle.

In conclusion, we prove that a single proxy architecture, which simplifies the Shuttle design by globally order the requests, is adequate.

5.3.2 Recovery

We measured the performance of the recovery process. We do not consider a particular scenario or replay scheme (full/selective) but define instead the number of requests recovered per experiment.

The recovery process can be summarized in the following points:

- Generate the list of requests to replay;
- Launch replay instances; Launch new application servers and database instances, if instance rejuvenation is used;
- Replay the requests.

The main factors of influence on recovery performance are: 1) the number of requests to replay, which depends on the request arrival rate; 2) the detection delay; 3) the number and type of database operations of each request.

We setup a test environment with 6 *c3.xlarge* instances in an AWS *Virtual Private Cloud* (VPC), sharing the same placement group (Figure 5.5). The first instance runs the *TryOut* testing application. The second runs Shuttle's manager, replay and Shuttle Storage (Cassandra). The third contains the application server WildFly with the application *Ask*. The last instance runs the database.

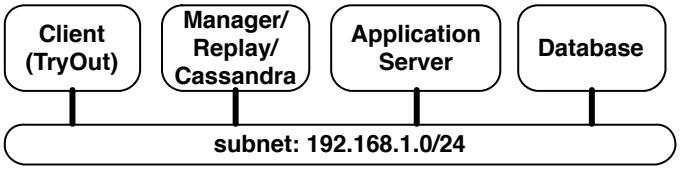


Figure 5.5: Instances deployed on AWS

We considered a workload of 95% reads, 5% inserts (StackExchange network has a read/write ratio of 98.82%). We consider a subset of *StackExchange Data Dump* [93] with 50 000 insert request (1432 questions, 3399 answers, 8335 comments, 36834 votes). Therefore, we consider a total of 1 million requests. The selected questions had 899 407 views in StackExchange. We consider 950 000 view requests.

TryOut performed the 1 million requests in 672 seconds on average (1486 requests/second, standard deviation of 20 seconds) using 25 concurrent threads (Figure 5.6). The average response latency

was 15.82 ms (90th percentile of 22.826 ms and 95th of 27.721 ms). The resultant dependency graph has 1 million entries that establish 9 425 579 dependencies.

5.3.2.1 Graph

The list of requests to replay is generated using the dependency graph. A *c3.xlarge* instance can insert 1 million requests, each depending from other 10 requests, in the graph in 6 seconds (166 000 requests per second). If each request depends on 2 other requests, then the same process takes 2 seconds. Each new request is represented as a novel entry in a Hash Table and each dependency requires modifying other entry (as the graph implementation is undirected). For web-scale applications, the dependency graph shall be implemented on a distributed hash table because of the graph storage requirements.

The period to generate the execution list is defined by the time to sort the keys of the dependency graph hash table and copy the list. We sort the keys using Java's sorting algorithm, dual-Pivot Quicksort, which has a asymptotic complexity of $\mathcal{O}(n \log n)$ for most of the data sets. On serial replay mode, the algorithm takes 150 ms (standard deviation of 31ms) to sort a dependency graph with 1 million entries and 279 ms (standard deviation of 24ms) to copy the sorted list. On clustered replay mode, the clustering algorithm takes on average 2218 ms (standard deviation of 1869 ms) to determine the 1432 independent clusters of the graph. Then, it takes 533 ms (std. dev. of 165 ms) to sort the clusters and copy the list.

5.3.2.2 Instance Rejuvenation

The time elapsed to launch a novel *c3.xlarge* instance in AWS depends on the current load of EC2. We measured 25 launches. The average time elapsed is 25 seconds (95th percentile of 40 sec). The time to deploy and launch the application depends on the application itself. The *Ask* application is launched in less than 1 minute. The process is done by the PaaS controller. We consider these delays negligible comparing with the total recovery period.

5.3.2.3 Request Replay

We performed full-replay considering a single-cluster of 1 million requests in 30 minutes (1717s or 584 requests per second) (Figure 5.6). The average request rate is 726 requests per second (std. dev. 72).

The performance is improved when considering 1432 independent clusters: 9 minutes (544s or 1795 requests per second) (Figure 5.6). Despite the fact that independent clusters can be replayed concurrently, we consider the maximum of 30 clusters being replayed concurrently. The average throughput is 1966 requests per second (std. dev 224).

The serial replay mode is not capable of fully exploring the application servers. While the first execution is performed using 25 client-threads and clustered replay using 30 client-threads, the serial replays uses one client-thread. We expect to solve this performance issue on future implementations.

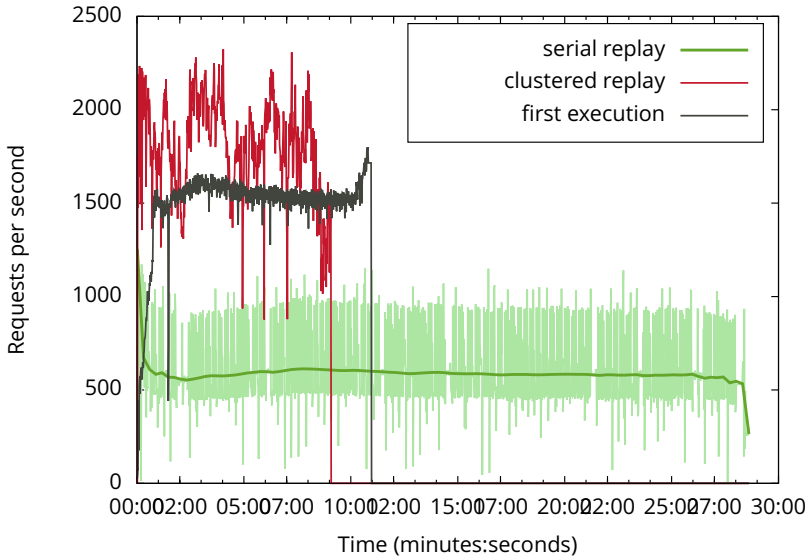


Figure 5.6: Recovery period without new incoming requests

5.3.2.4 Restrain

We measured the duration of the restrain period considering two clients with a constant throughput of 400 requests/sec (Figure 5.7).

Considering serial replay, the average response time of new incoming requests is 3.94 ms (95th percentile of 10.34 ms, 90th of 7.53 ms). Since the serial replay mode is not capable of fully exploring the application servers, the new incoming requests are not affected by the replay process. The replay process takes on average 30 minutes (1850 ms). Since the Shuttle takes 30 minutes to replay 1 million requests, the new flow generates 298 thousand new requests. Shuttle takes 18 minutes to replay these new requests. The user requests are suspended until the new requests are replayed and the branch is changed. This delay is considerable because the throughput of new requests is close to the throughput of the requests being replayed. The delay can be reduced by replaying the new requests and then block to replay the newer requests, i.e., creating several phases of replay. fazer varias fases, cada vez mais curtas porque vai compensando a diferenca. In addition, if the replay rate is bigger than the rate of new incoming requests, then the restrain phase is shorter.

If Shuttle performs clustered replay, the application servers are overloaded. Consequently, the average response time of new incoming requests is 5.51 ms (95th percentile of 13.56 ms, 90th of 10.60 ms) and the throughput of the new incoming requests drops from 200 to 95 requests per second. On other hand, the throughput of requests being replayed drops from 1795 to 1686 req./sec. The recovery process takes a total 10 minutes (635 seconds). Therefore, the customers perform 56 000 requests. These requests are replayed in 46 seconds (Figure 5.8).

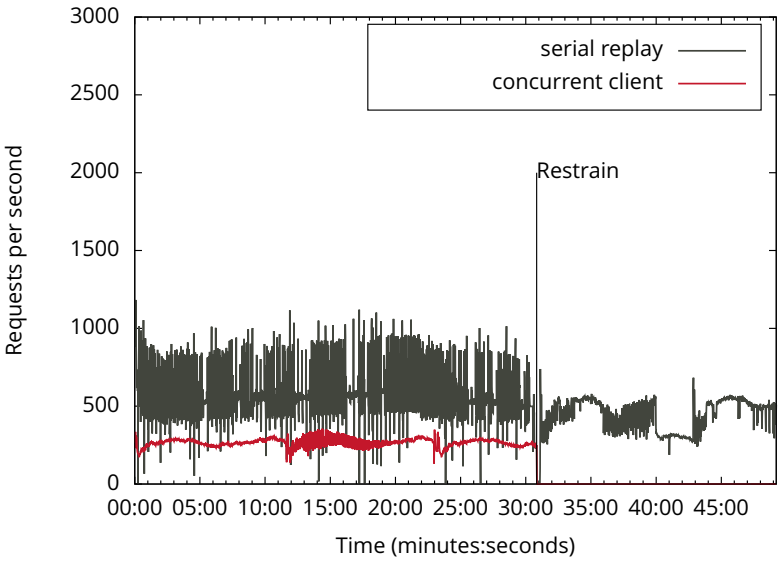


Figure 5.7: Serial Recovery: Requests throughput during the recovery period

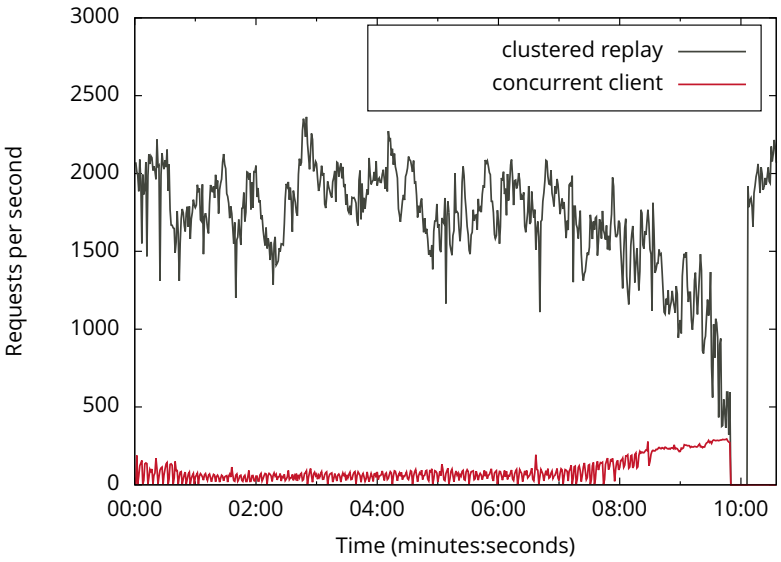


Figure 5.8: Clustered Recovery: Requests throughput during the recovery period

When a new application server is added, the throughput of the requests being replayed rises from 1686 to 2517 requests per second (397 seconds to recover), while the response latency to new requests is 4.61 ms. Therefore, we prove that adding more servers to perform replay allows to keep the quality of service for the customers.

5.3.2.5 Scalability

We measured how Shuttle leverages the horizontal scalability (adding more instances) of PaaS to reduce the recovery period. We added *c3.large* instances c3.large (7 ECUs, 2 vCPUs, 2.8 GHz, Intel Xeon E5-2680v2, 3.75 GiB memory, 2 x 16 GiB Storage Capacity). The application server *c3.xlarge* instance was downgraded to *c3.large*.

The serial replay with 2 application servers and 1 database takes 1347 seconds, while with 2 ap-

plication servers an 2 database instances takes 1303 seconds (Figure 5.9). At larger scale, considering 2 databases, 6 application servers and 2 Shuttle storage instances, the process takes 1745 ms. Therefore, due to its implementation, the serial replay does not scale well. All instances remain with low resource usage. We expect to do much better by rewriting the implementation of the serial replay in the replay instances.

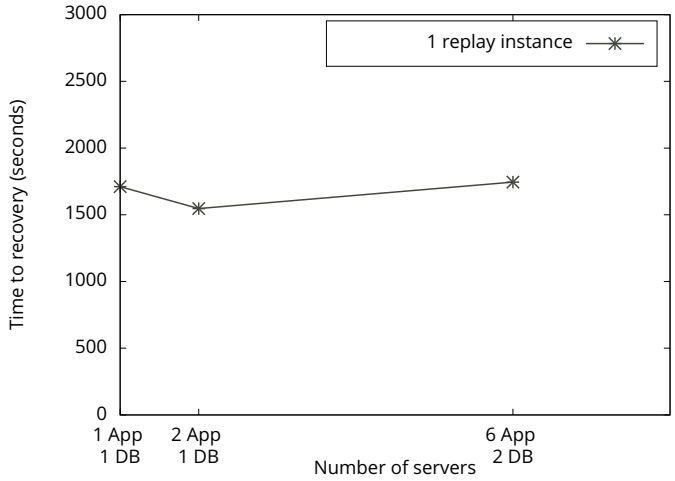
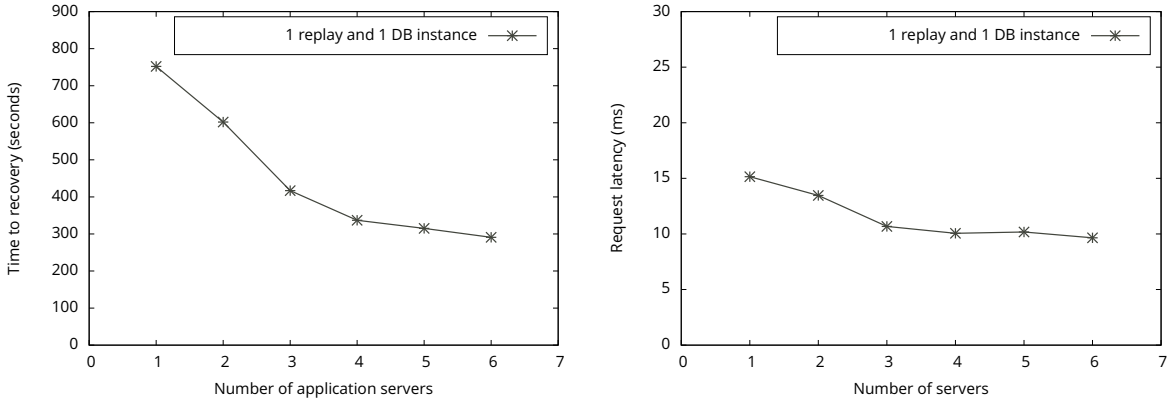


Figure 5.9: Shuttle Scalability Serial

The Figure 5.10 (detailed values in Appendix B.1) shows the recovery time using clustered replay. The figure demonstrates that Shuttle is scalable, in the sense that adding more servers allow reducing the time of recovery. Three application servers allowed recovery in half the time of one (750 versus 417 seconds). If the application runs on 5 or more application servers, then the single Shuttle Storage (Cassandra) instance becomes the bottleneck because Shuttle database client interceptor fetches the keys accessed by every request. We added another *c3.xlarge* instance to the Cassandra cluster.

The latency of the requests during their first execution remains approximately constant when 3 servers are added (Figure 5.10b). This means that a single *TryOut* instance performing 2000 requests per second is not capable of overstraining the resources of the application servers.

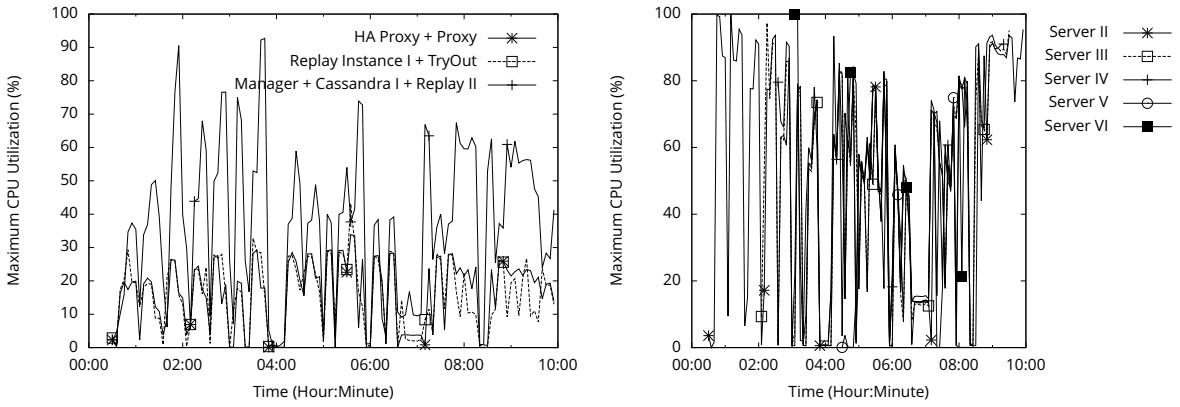


(a) Recovery time (Clustered replay)

(b) Response latency on first execution

Figure 5.10: Shuttle Scalability

When using less than 6 application servers, adding more database instances or clients does not improve the performance. When supporting 3 application servers, the CPU usage of Voldemort database remains at 10% on average. The CPU usage of the instances that contain Shuttle's modules remains low (Figure 5.11a). The bottleneck is the CPU usage on the application servers (Figure 5.11b).



(a) CPU usage of Shuttle's instances

(b) CPU usage of Application instances

Figure 5.11: CPU Usage during several execution and replay phases

We conclude the application servers to be the main performance harm. The performance of the application servers can be improved. If application developers for PaaS optimize their applications to execute more requests per unit of time, then the recovery period is reduced. Most of PaaS controller watch the load of the instances. One area of future development is to dynamically adapt the throughput of the replay instances to the load of the application and database instances.

5.3.3 Space Overhead

The storage overhead is relevant because it is a payed cloud resource and Shuttle stores every user request. The space overhead is defined by the variables in Table 5.8.

Module	Contains	Depends on
Shuttle Storage		
	Request	request content
	Response (optional)	response content
	Accessed keys	key size and number of database operations per request
	Start and end instants	constant overhead
Database instance		
	Version list	number of snapshots per data item
	Operation list	number of operations per data item
Dependency graph		
	Dependencies	number of dependencies per request

Table 5.8: Variables on Shuttle's storage

Requests to static contents, e.g., images, are ignored. For instance, a question page of StackOverflow [94] implies 30 static content requests. Shuttle is not implemented for web-services with large requests, such has file hosting services, because the data would be duplicated in the requests and storage. Shuttle architecture would remain similar on those services but would require an algorithm

to reduce the storage overhead by detecting duplicated data.

Most of applications' requests, including headers, vary in size from 200 bytes to over 2KB, depending on the number of application cookies [101]. As applications use more cookies and user agents expand features, typical header sizes of 700-800 bytes are common [101]. Shuttle adds the SRD, which has 35 bytes, to every request. Requests of *Ask* based on the StackExchange Network have an average size of 216 bytes (std. def of 124 bytes, 95th percentile of 274 bytes, 99th of 494 bytes in a sample of 200 thousand requests, in which 95% are read requests).

Requests and keys are stored in the *Shuttle storage* (Cassandra) while the dependency graph and database operations are kept in manager and database instances. Values at Table 5.9 represent the size of each component in memory [1] to store the workload, defined above (1 million requests, from which 95% are requests to read a question). No snapshot has been taken and the data is not compressed.

	# objects	size (total) (MB)
Shuttle Storage:		
Request	1 million	212
Response	1 million	8 967
Start/End	2 million	16
Keys	137 million	488
Total		9 684
Database node:	14 593 entries	
Version List	14 593	1.4
Operation List	9 million	277
Total		282
Manager:		
Graph	1 million	718

Table 5.9: Storage used by Shuttle

The start/end instants have a constant size of 16 bytes because each timestamp is a long. The size of the list of keys accessed by the request depends on the key length and the number of accesses. The request of the workload defined above represent 212 MBytes. The main overhead are the requests, as we are storing them complete (the full HTTP pages). Notice that Shuttle has to store the responses only if the tenants use the API to solve inconsistencies (Section 3.5.7). In addition, the size of the responses can be reduced if applications fetch only data using a *Representational State Transfer* (REST) API instead of the entire page.

Since HTTP messages are similar, we evaluated how a compression technique can reduce the storage usage. While Cassandra stores 9GB of data, the compression algorithm of Cassandra, *lz4* [102], reduces the size in disk to 4.9 GB (including Cassandra's metadata). For instance, considering an arrival rate of 1000 requests per second (86 million per day), a half-year (15.638 billion requests) requires 3.3 TB.

The snapshot mechanism requires to track a new version when a data item is written by the first time after a snapshot. Each version has 10 bytes. The overhead can be reduced implementing the

[1] https://code.google.com/p/memory-measurer

version list as a bitmap. In addition, each database operation implies to store 13 bytes to record its RID and type in the *operation list*. The total database storage overhead encompasses synchronization mechanisms and object references. Notice that the storage and performance overhead can be distributed by several instances because the data items are independent.

The dependency graph is a double-linked graph implemented as a Hash Table. Each of its entries represents a request. It contains the start and end instants of the requests and two lists of RID: requests to execute before, requests to execute after. Each entry in the Hash Table has, on average, 718 bytes bytes, and depends on 1 requests and 5 requests depend on it (Table 5.10). The start and end instants has 32 bytes. Each dependency has 16 bytes.

For the sake of performance in selective replay, the dependency graph is doubly-linked, a single-linked graph requires, on average, 458 bytes per entry. In order to reduce the storage overhead, a doubly-linked graph can be generated from a single-linked graph.

	# objects	**size (bytes)**
Start	1	16
End	1	16
Before	1	61
After	5	162
Total	-	718 MB

Table 5.10: Memory used by each entry of dependency graph

Tenants can reduce the storage overhead removing old snapshots, operations and requests. However, they shall take into account that Shuttle needs a snapshot previous to the intrusion instant to recover the application.

In conclusion, the main storage overhead are the HTTP responses. We propose several ways to reduce the storage overhead. Since the data stored by Shuttle is likely to be similar, compression techniques can reduce the storage overhead.

5.4 Monetary Cost

We measured the monetary cost of the intrusion recovery process using a public cloud provider. The intrusion recovery costs are come from two sources: storage and computation resources. The following prices represent the current cost of AWS in North Virgina.

We consider an execution of *Ask* application with a constant arrival rate of 250 requests per second (20 million per day) and the storage usage defined in Section 5.3.3. This is a common rate for an enterprise application, for instance the Portuguese Ministry of Finances (Table 5.3). We also define that Shuttle shall allow to recover from attacks that have occurred during the last 3 months. Therefore, Shuttle needs to store 2 billion requests. We assume that the recovery process re-executes 50 million requests, independent of the schema (full/serial replay).

Table 5.11 represents the estimated storage overhead based on the measurements introduced in

Section 5.3.3. We do not consider Shuttle to store the responses.

	1 million	20 million (day)	2 billion (quarter)
Shuttle Storage	716 MB	14.32 GB	1.432 TB
Graph	718 MB	14.36 GB	1.436 TB
Database Nodes	282 MB	5.64 GB	564 GB

Table 5.11: Storage overhead considering different number of stored requests

The user requests can be stored in AWS S3, DynamoDB, Glacier and *Elastic Block Store* (EBS) (Table 5.12). *S3* is a scalable object storage, *EBS* block level storage, *Glacier* low-cost storage service for data archiving and online backup, *DynamoDB* low-latency NoSQL database. Their usage costs are also distinct (Table 5.13).

Data per month	Cost per GB-month			
	S3	Glacier	EBS	DynamoDB
First 1 TB	$0.0300	0.0100	0.05	0.25
Next 49 TB	$0.0295	0.0100	0.05	0.25
Next 450 TB	$0.0290	0.0100	0.05	0.25
Next 500 TB	$0.0285	0.0100	0.05	0.25
Next 4000 TB	$0.0280	0.0100	0.05	0.25
Next 5000 TB	$0.0275	0.0100	0.05	0.25

Table 5.12: Pricing of Amazon Web Services S3, Glacier, EBS and DynamoDB

Operation	Usage cost per month			
	S3	Glacier	EBS	DynamoDB
Put	0.005 (1k ops)	0.050 (1k ops)	0.05 (1M ops)	0.0065 (Hour)
Get	0.0004 (1k ops)	0.01 (1 GB)	0.05 (1M ops)	0.0065 (Hour)

Table 5.13: Usage cost of Amazon Web Services S3, Glacier, EBS and DynamoDB

Glacier has the lowest cost to store data for long period but the highest per insert operation. In contrast, DynamoDB provides the lowest cost per insert operation, lower latency but the highest per stored gigabyte. The best storage model depends on the application usage pattern. We propose to store the most recent data in *DynamoDB* and archive the data in periodically in *Glacier*. We assume that the data in DynamoDB is archived every day, i.e., each batch stores a day.

Shuttle generates an average of 35 GB per day, which costs $8.75 per month to store in DynamoDB. Considering a provisioned capacity of 36,000 writes per hour and 180,000 strongly consistent reads per hour, the DynamoDB usage costs $4.83 per-month.

The Glacier stores 3.433 TB, which represents the archives of the latest quarter, so it costs $34.33 per month. Since the daily backup can be compressed in a single file, the number of put requests per month is lower than 1 thousand so it costs less than $0.05. Tenants can retrieve up to 5% of average monthly storage for free. Since we consider an attack that taint 1 million requests, the required download of 2 GB is free. This data is loaded in DynamoDB to perform the replay process.

In total, the storage overhead of Shuttle costs $47 per month if the application retrieves 20 million requests per day.

	vCPU	ECU	Memory (GiB)	Instance Storage (GiB)	Cost per Hour
t2.small	1	Variable	2	EBS Only	$0.028
t2.medium	2	Variable	4	EBS Only	$0.056
m3.medium	1	3	3.75	1x4 SSD	$0.077
m3.large	2	6.5	7.5	1x32 SSD	$0.154
m3.xlarge	4	13	15	2x40 SSD	$0.308
m3.2xlarge	8	26	30	2x80 SSD	$0.616
c3.large	2	7	3.75	2x16 SSD	$0.120
c3.xlarge	4	14	7.5	2x40 SSD	$0.239
c3.2xlarge	8	28	15	2x80 SSD	$0.478
c3.4xlarge	16	55	30	2x160 SSD	$0.956
c3.8xlarge	32	108	60	2x320 SSD	$1.912

Table 5.14: Pricing of Amazon Web Services EC2 Instances

Since Shuttle is designed to be integrated with the cloud provider infrastructure, namely the load balancer and the database, the costs of the database and proxy overhead are hard to predict. The Shuttle manager is also included in the underlying cloud provider infrastructure and can be shared by multiple clients.

The Table 5.14 represents the costs of the computation instances in AWS. The data transfer between computing instances and the database is free in the same region using private IP addresses.

In Section 5.3.1, we demonstrate that Shuttle requires two extra *c3.xlarge* instances: the manager and the proxy. To recover the application, Shuttle can replay 1 million requests in 400 seconds using 5 application servers (*c3.large* instances) and 1 *c3.xlarge* replay instance.

Considering a full-hour, these instances have an associated cost of $1 per instance-hour, which means that Shuttle can replay 1 million requests by the cost of $1. Since Shuttle allocating more instances reduces the recovery period, Shuttle leverages the elasticity and pay-per-usage model of cloud computing to provide a cost-efficient intrusion recovery solution.

In conclusion, the cost of Shuttle is dominated by the storage because the replay instances are allocated on demand and paid-per usage.

Notice that the costs are estimations for the application prototype and vary with the type and usage of the tenants applications. In addition, Shuttle aims to be integrated as a service in the public CSP infrastructure: the proxy is integrated into the load-balancer and the database proxy is integrated in the database instances. Each manager and Shuttle storage can be shared by several tenants. Therefore, we expect providers to define a pay-per-usage model of Shuttle service. In addition, providers can reduce the costs because the data stored by several tenants is similar thus can be compressed. We do not address the creation of a pay-per-usage model in this document but we would like to address it in our future research.

5.4.1 Discussion

In this section we measured the performance overhead, the duration and scalability of the recovery process, the storage requirements and the cost of the used resources. We evaluated Shuttle

usage for the prototype application *Ask*. Shuttle is designed to support various PaaS applications with distinct semantics.

The evaluated metrics depend on several aspects of the application. Taking into account all that was mention, we identified the following factors to be the most relevant:

1. Request rate
2. Request/response size
3. Detection delay
4. Dependency between requests
5. Number of operations per request

Clearly, much future research and development will be needed to create a version of Shuttle for web-scale applications. The performance of Shuttle modules can be optimized and tunned to archive better performance and lower storage footprint, reducing the costs and recovery period.

Nevertheless, we validated our single proxy architecture. The proxy imposes a throughput limitation but this limitation is acceptable for most of applications. Moreover, this limitation does not affect the recovery period.

We presented a cost estimation for Shuttle usage. In future, we expect to provide a generic pricing model that CSP can use to provide Shuttle on a pay-per-usage manner.

5.5 Chapter Summary

The main conclusions of the Shuttle evaluation presented in this chapter are:

1. The full replay has lower precision than selective replay but the recovery time is acceptable and allows to remove malicious actions not logged by the proxy.
2. The prototype accuracy and performance is acceptable for small and enterprise applications.
3. It is possible to duplicate the number of requests replayed per second by increasing the number of application servers from 1 to 3.
4. The main storage overhead is the response storage but the data can be compressed.
5. The usage cost of Shuttle is low considering its advantages.

6

Conclusion

This dissertation described Shuttle, the first intrusion recovery system for PaaS that uses a record-and-replay approach. We aim to define a generic architecture that allows CSP to offer an intrusion recovery system as a service to their tenants. This service is available without setup and can be provided in a pay-per-usage manner. Our research focused on developing a scalable service to meet the intrusion recovery of Cloud tenants. The success of Shuttle will be measured mostly by the impact of two of this dissertation's main contributions: a service integrated in PaaS that leverages the resource elasticity and pay-per-use model and a new process to establish the requests' order during the replay process.

This chapter reflects on these contributions, discusses future work and concludes.

6.1 Conclusions

Our approach to develop an intrusion recovery system for cloud computing focus on restoring the applications integrity when intrusions happen, instead of trying to prevent them from happening. Previous works address this problem at operating system level [24, 25] or distributed systems [30]. These systems might be adapted to recover from intrusions in the IaaS model. Other works aim to recover databases [26, 27] and web services [28–30], so they can be adapted to recover services delivered in the *Software as a Service* (SaaS) model. The closest research to ours is Undo for Operators (UO) [31]. Both works address the problem of providing a generic intrusion recovery system. However, UO requires tenants to configure the dependencies and order for each possible operation of the application's protocol. Our approach does not require configuration. Nevertheless, none of the previous works does recovery in cloud environments. We consider an intrusion recovery system to be a significant asset for CSPs because they are responsible for managing the PaaS applications and

ensure their security. The PaaS model imposes novel challenges because its applications scale and run in various instances backed by distributed databases.

Having the above in mind, we proposed Shuttle, an intrusion recovery service for PaaS, that aims to make PaaS applications operational despite intrusions. Shuttle recovers from software flaws and corrupted requests. As consequence of its architecture, our solution also supports preventive maintenance and to test the application with real user requests. Shuttle loads database snapshots to remove the intrusion effects and replays the legitimate user requests to recover the application integrity.

In order to remove the intrusion effects, we proposed a novel method to perform snapshots of NoSQL databases. This method, which is based on copy-on-write, performs globally transaction-consistent and incremental snapshots without system downtime. We also proposed a novel process that redeploys tenants' application in new application instances to remove all intrusions in the previous instances and update their software versions to fix previous flaws or prevent future vulnerability exploitations.

In order to restore the application integrity, we proposed a new method to re-execute requests. This method supports that the requests have been executed concurrently. It replays the requests on the same order than on their first execution and constrains the execution order using the list of operations performed on each database item. Since database items are independent, our replay algorithm is scalable. In addition, we proposed a semantic-reconciliation mechanism to solve conflicts during the recovery process.

Previous works use the dependency graph to establish the requests order. Instead, we use it to create independent clusters of requests that can be re-executed concurrently. We evaluated that this technique reduces the recovery period considerably.

We accomplish intrusion recovery without service downtime using a branching mechanism.

In summary, the proposed architecture is capable of leveraging the resource elasticity and pay-per-use model in PaaS environments to record and launch multiple clients to replay previous non-malicious user requests as concurrently as possible to reduce the recovery time and costs.

Thus, we have achieved the goal we set out at the beginning of this dissertation: help CSP customers to recover from intrusions in their applications deployed in PaaS.

6.2 Future Work

The following directions are proposed as a development of the present research:

- Propose mechanisms to prevent intrusions from spreading.
- Take into account client side applications' code and user sessions. How an intrusion recovery system can leverage them to establish dependencies between requests?
- Consider more database schema and complex operations, e.g., scan and append, and idempotent operations. How the replay algorithms can encompass them?

- Fault-tolerance: how to handle instance failures during the recovery process? How to handle database replication?
- Propose a pricing model to deliver a intrusion recovery system on a pay-per-usage manner.
- How the instance rejuvenation can be used in PaaS to prevent attackers from compromise a quorum of replicas.

In addition, we propose to develop an user interface for tenants and evaluate their experience. A distinct research direction can evaluate how intrusion recover system for cloud, such as Shuttle, can be integrated and affect the recovery procedures of companies. In particular, how these systems can be integrated and used by the practices, for instance, defined in the Service Design and Service Operation aspects of *Information Technology Infrastructure Library* (ITIL). By doing so, we expect to analyze the advantages and disadvantages of using these services.

The major challenges to implement the current prototype were: concurrent and consistent database snapshot, establish accurate requests dependencies, perform parallel actions replay, repair the system state in time, avoid application downtime and keep the application source code unmodified as much as possible.

As future work, we would like to improve the implementation by:

- Optimize the concurrency mechanisms serial replay in the replay instances.
- Migrate the dependency graph to a distributed database.
- Improve the clustering algorithm.
- Integrate the proxy in a load-balancer implementation.
- Analyze compression mechanisms to reduce the memory and storage footprint.

Shuttle removes intrusions' effects in PaaS applications and restores their state to an intrusion-free state. We propose, to the best of our knowledge, the first intrusion recovery service for PaaS and the first to support NoSQL databases.

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Messages

A.1 Voldemort Client API

```
message KeyedVersions {
  required bytes key
  repeated Versioned versions
  optional MsgToManager.SRD srd
}

message GetRequest {
  optional bytes key
  optional bytes transforms
  optional MsgToManager.SRD srd
}

message GetResponse {
  repeated Versioned versioned
  optional Error error
  optional MsgToManager.SRD srd
}

message PutRequest {
  required bytes key
  required Versioned versioned
  optional bytes transforms
  optional MsgToManager.SRD srd
}

message PutResponse {
  optional Error error
}

message UnlockRequest {
  repeated bytes key
  optional MsgToManager.SRD srd
}

message UnlockResponse {
  repeated KeyStatus status
  optional Error error
}
```

A.2 Shuttle messages

```
// From manager to database instances
message ToDatabaseInstance{
  optional int64 newSnapshot
  optional bool replayOver
  repeated int32 pathBranch
  repeated int64 pathSnapshot
}


// From manager to replay instances
message ExecList{
  repeated int64 rid
  required int32 branch
  required bool start
  required string replayMode
  required string targetHost
  required int32 targetPort
}


// From manager to proxy
message ProxyMsg{
  optional int32 branch
  optional bool restrain
  optional int64 timeTravel
  optional int64 snapshot
}


// To Manager
message MsgToManager{
  optional TrackMsg trackMsg
  optional StartEndMsg startEndMsg
  optional NodeRegistryMsg registry
  optional AckMsg ack
  repeated EntryAccessList accesses
  optional AckProxy ackProxy

  // From database nodes
  message TrackMsg{
    repeated TrackEntry entry
    optional string nodeId

    message TrackEntry {
      required int64 rid
      repeated int64 dependency
    }
  }

  // From proxy
  message StartEndMsg{
    repeated int64 data
  }


  message SRD{
    optional int64 rid
    optional int32 branch
    optional bool restrain
    optional bool replay
  }


  // From Replay Nodes
  message AckMsg{
    optional int32 port
    optional string hostname
    repeated string exception
  }


  message AckProxy{
    required int64 currentId
  }


  // From any instance
  message NodeRegistryMsg{
    enum NodeGroup{
      PROXY
      DB_NODE
      REDO_NODE
    }
    required NodeGroup group
    required int32 port
    required string hostname
  }

  message EntryAccessList{
    required bytes key
    repeated int64 rid
  }

}

enum RequestType {
  GET
  GET_ALL
  PUT
  DELETE
  GET_VERSION
  UNLOCK
}
```

B

Measurements

B.1 Recovery performance

App	Replay	DB	Cassandra	Duration to Replay (secs)	Duration of First Execution (secs)	Latency of First Execution (ms)
1	1	1	1	947 [1055]	1171[853]	27.5 [54.09]
2	1	1	1	602 [1658]	655 [1525]	15.15 [26.68]
2	2	2	2	575[1739]	777 [1286]	18.14 [36.36]
3	1	1	1	417 [2392]	586 [1705]	13.46 [24.18]
3	2	2	2	380 [2631]	541 [1848]	15.21 [26.12]
4	1	1	1	337 [2959]	473 [2112]	10.68 [17.85]
4	2	2	2	335 [2985]	452 [2212]	11.12 [15.54]
5	1	1	1	342 [2921]	447 [2235]	10.06 [16.95]
5	1	1	2	315 [3164]	493 [2025]	11.18 [18.80]
5	2	2	2	297 [3367]	505 [1980]	12.21 [17.22]
6	1	1	2	291 [3434]	453 [2005]	10.18 [16.73]
6	2	1	2	259 [3861]	436 [2293]	9.65 [16.24]
6	2	2	2	305 [3278]	493 [2026]	11.16 [18.77]

Table B.1: Recovery duration (request throughput between parenthesis). Duration and latency on first execution (request throughput and 95th percentile between parenthesis, respectively).