Swiper: Exploiting Virtual Machine Vulnerability in Third-Party Clouds with Competition for I/O Resources

Ron C. Chiang, Sundaresan Rajasekaran, Nan Zhang, and H. Howie Huang

Abstract—The emerging paradigm of cloud computing, e.g., Amazon Elastic Compute Cloud (EC2), promises a highly flexible yet robust environment for large-scale applications. Ideally, while multiple virtual machines (VM) share the same physical resources (e.g., CPUs, caches, DRAM, and I/O devices), each application should be allocated to an independently managed VM and isolated from one another. Unfortunately, the absence of physical isolation inevitably opens doors to a number of security threats. In this paper, we demonstrate in EC2 a new type of security vulnerability caused by competition between virtual I/O workloads—i.e., by leveraging the competition for shared resources, an adversary could intentionally slow down the execution of a targeted application in a VM that shares the same hardware. In particular, we focus on I/O resources such as hard-drive throughput and/or network bandwidth—which are critical for data-intensive applications. We design and implement *Swiper*, a framework which uses a carefully designed workload to incur significant delays on the targeted application and VM with minimum cost (i.e., resource consumption). We conduct a comprehensive set of experiments in EC2, which clearly demonstrates that Swiper is capable of significantly slowing down various server applications while consuming a small amount of resources.

Index Terms—Cloud computing, virtualization, scheduling

DORA the Explorer[1]*: "Swiper, no swiping!"*
Swiper the Fox: "You are too late."

1 INTRODUCTION

A cloud computing system offers to its users the illusion of "infinite" computing and storage capacities on an on-demand basis [1]. Examples of commercial cloud computing platforms include Amazon Elastic Compute Cloud (EC2) and Simple Storage Service (S3), Google AppEngine, Microsoft Azure, etc. Virtualization [2] plays a vital role in cloud computing. In particular, for the purpose of scalability and flexibility of resource delivery, a cloud computing system does not provide each user with a different physical machine—instead, it allocates each user to an independently managed *virtual machine* (VM) which can be dynamically created, modified, and migrated. Examples of such a platform include Xen VM for Amazon EC2 and the .NET-based runtime environment for Microsoft Azure.

The essence of virtualization is that multiple VMs may multiplex and share the same physical resources (e.g., CPU, cache, DRAM, and I/O devices). Nonetheless, each VM is supposed to enjoy *isolation* (in terms of security and performance) from the other VMs. That is, different VMs should *not* be able to interfere with the executions of each other.

Unfortunately, the lack of physical isolation can indeed pose new security threats to co-located VMs. In this paper, we consider a new type of VM vulnerability which enables a malicious user (i.e., VM) to exploit the resource contention between co-located VMs and obstruct the execution of a targeted application running in a separate VM that is located on the same physical machine as the malicious one. In particular, we focus on exploiting contentions on shared I/O resources that are critical to data-intensive applications—e.g., hard disks and networks. In practice, service providers often exclude such threats from their service level agreement (SLA) [3]. That is, customers are solely responsible for their loss caused by resource contention from co-located VMs. Most service providers do not enable dynamic migration for user control [4]. Even if a customer suspects an attack and wants to move affected VMs away, they need to shutdown and restart all affected VMs. Therefore, an attack from Swiper may incur nontrivial loss in business by introducing service degradation or interruption, e.g., Amazon.com would lose sales by 1 percent for every 100 ms delay in page load time and a similar test at Google also revealed that a 500 ms increase in displaying the search results could reduce revenue by 20 percent [5].

Note that the main concern of this work is performance degradation caused by co-located adversaries, rather than

1. Swiper the Fox is a cartoon character in the animated series of Dora the Explorer, who often sneaks up to Dora and Boots and takes away the items that are needed for Dora's adventures.

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information leakage which has been the main focus for vulnerability studies in cloud-computing systems [6]. Performance degradation is critical because it directly increases the cost of per workload completed in cloud [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18]. On the other hand, the existing work on performance-degradation analysis were conducted on non-virtualized environments (e.g., for CPU, DRAM, hard disk, and network usage [19]) and cannot be directly applied to VMs. For example, a relevant prior work that proposed to exploit the contention on hard-disks [20] required access to the hard-disk queue in order to analyze the requests from both the adversary and the victim. However, this queue cannot be directly accessed by VMs, rendering such exploitation no longer applicable.

In this work, we design and implement *Swiper*, a framework that exploits the virtual I/O vulnerability in three phases: 1) *co-location ("sneaking-up")*: place the adversary VM on the same physical machine as the victim VM; 2) *synchronization ("getting-ready")*: identify whether the targeted application is running on the victim VM and, if so, the state of execution for the targeted application (which we shall elaborate below); and 3) *exploiting ("swiping")*: design an adversarial workload according to the state of the victim application, and launch the workload to delay the victim.

The main contributions of this paper are listed as follows:

- An I/O-based co-location detection technique and verified its effectiveness on public clouds.
- A discrete Fourier transformation (DFT) based algorithm which recovers the victim's original I/O pattern from the observed (distorted) time-series of I/O throughout, and then determines if the victim application has reached a pre-determined point when it is most vulnerable to an exploitation.
- Discover patterns which cause maximum interference.
- A theoretical framework to observe and synchronize with predefined I/O patterns.
- A comprehensive set of experiments on Amazon EC2—with the results clearly showing that Swiper is capable of degrading various server applications by 22.54 percent on average (and up to 31 percent) for different instance types and benchmarks, while keeping the resource consumption to a minimum.

The remainder of this paper is organized as follows. Section 2 introduces the system and threat models. Section 3 presents our IO-based co-location detection method. Section 4 describes our approach, and explains the synchronization and exploiting stages. Section 5 discusses issues in practicing Swiper. Section 6 presents the experiments and results, including VM co-location in Amazon EC2. We conclude in Section 7. Interested readers may also access the Appendices, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TPDS.2014.2325564, for additional details on the design, implementation and evaluation.

2 Threat Model

In general, a cloud computing system provides its end-users with a pool of virtualized computing and I/O resources supported by a large amount of distributed, heterogeneous, commodity computers. For example, Amazon EC2 is using Xen virtualization, whose architecture and terminology are described in Appendix A, available in the online supplemental material.

For I/Os, VMs utilize the device drivers (the frontend drivers) in the guest OS to communicate with the backend drivers in DOM_0, which access the physical devices, e.g., hard drives and networks, on behalf of each VM. In other words, application I/Os within a VM—which basically consist of block reads and writes to the virtual disks—are translated by the virtualization layer to system calls in the host OS, such as requests to the physical disks. In Xen, the hypervisor and DOM_0 work together to ensure security isolation and performance fairness among all VMs. While fairness in CPU and memory virtualization is relatively easy to achieve, in this paper we show that maintaining performance isolation for virtual I/O can be extremely challenging—which opens doors for security threats.

In this work, we also evaluate our framework on Kernel-based Virtual Machine (KVM) that utilizes hardware assisted full virtualization instead of Xen's paravirtualization. Although Xen and KVM are used to demonstrate this threat in our work, our test and previous work indicate that other virtualization framework like VMware also exhibits similar interference problem [21].

2.1 Problem Definition

A straightforward way to delay a victim process is to launch an attacking process which constantly requests a large amount of resources shared with the victim (e.g., I/O bandwidth). Nonetheless, such an attack can be easily detected and countered (e.g., a dynamic resource allocation algorithm can restrict the amount of resources obtained by each process). Thus, our focus in this paper is to incur the maximum delay to the victim while maintaining the resource request from the attacker to a pre-determined (low) threshold.

Prior knowledge of the adversary. Since the adversary now has to target the attack specifically to the victim process (instead of blindly delaying all processes sharing the resource), it has to possess certain characteristics of the victim process which distinguishes it from others. For the purpose of this paper, we consider the case where the adversary holds the trace of resource requests from the victim process as the "fingerprint" of the victim.

Research on cross-VM side channels can be used to sustain this assumption [22], [23], [24], [25]—malicious VMs are able to retrieve a variety of information, such as data and instruction caches, I/O usage profile, and even private keys, from co-located VMs and hosts via side channels. The techniques for co-location detection in Section 3 can also be adapted to profile I/O access patterns as well. We plan to extend the profiling technique as future work. In the experiment section, we shall demonstrate that the various workloads we tested all exhibit unique resource-request time-series that can be easily distinguished from others.

Limits on the adversary. Many cloud computing systems charge by the amount of resource requests. For example, Amazon Elastic Block Store (EBS) charges \$0.1 - \$0.11 per 1 million I/O requests and Amazon EC2, on the other hand,

charges by total network consumption—i.e., the amount of data transferred in and out of the system [26]. Thus, the adversary must minimize the amount of resource request initiated by itself. In this paper, we consider a pre-determined upper bound on the total resource consumption by the adversary.

Problem Statement. Given a workload fingerprint of a victim process, determine an adversarial workload of I/O request which incurs the maximum delay on the victim process without exceeding the pre-determined threshold on the adversary's own resource consumption.

3 I/O-Based Co-Location Detection

In this work, we use Amazon EC2 as one testing platform to carry out experiments. As we focus on vulnerability with competition for I/O resources, we choose two types of Amazon EC2 instances, *micro* and *small*, to be the experiment instance types. Please refer to Appendix B, available in the online supplemental material, for the introduction of Amazon EC2.

The co-location detection mainly consists of two stages: *Probing* and *Locking-on*.

Probing. An adversary can locate the geographical zone of a victim process by the victim's IP information [6]. To conveniently manage separate networks for all availability zones, Amazon EC2 partitions internal IP address space between availability zones. Administration tasks will be more difficult if the internal IP address mapping changes frequently. Because different ranges of internal IP address represent various availability zones and public IP addresses can be mapped to private IP addresses by DNS, an adversary can easily locate the availability zone of a victim, thus greatly reduce the number of instances needed before achieving a co-location placement.

Once an adversary knows the availability zone of a victim, it uses network probing to check for the co-residence. In general, if an adversary and a victim are co-located, they are likely to have 1) identical DOM_0 IP address, and 2) small packet round-trip times (RTT).

Therefore, an adversary can create several probing instances to perform a TCP SYN traceroute operation to a victim's open service port. If one probing instance and the victim were co-located, they would share the same DOM_0 and there would be only a single hop to the victim with a small RTT. In our experience, if the RTT is smaller than half of the average RTT of all one-hop instances in the same zone, the probing instance is very likely on the same physical machine as the victim.

Locking-on. Co-location on the same physical machine does not necessarily mean the sharing of the I/O resources—co-located VMs may end up using different storage types. In our tests, if two co-located VMs do not share one hard drive, launching a workload to compete for I/O resources shows limited effect on I/O throughput. On the other hand, if two instances share the same storage device and both try to max out the bandwidth, they can only get part of the total bandwidth. Prior works also have shown similar interference effect in virtualized environments [27], [28], [29].

Because the adversary knows its performance under a given I/O workload, for it to confirm the I/O sharing, it needs a VM instance that would potentially co-locate with the victim and try to compete for I/O resources. The adversary then can simply measure the I/O performance and an obvious performance degradation would be a strong indicator of VM co-location.

The proposed lock-on approach is feasible on public clouds. For example, our experiments on Amazon EC2 us-east-1c zone show the success rates of about 8 and 2 percent for the probing and the locking-on stages respectively. After locking-on a victim, a smart adversary does not just launch a huge workload to compete for resources. This naive method leads to ineffective attacks and wastes time and money. Therefore, we develop a synchronization method in the following sections to assure accurate attacking time. As we will show later, this method generates a more severe performance degradation and uses less resources than the naive method.

4 Swiper for a Two-Party System

We start with a simple scenario where the resource is only shared between two parties, i.e., the attacker and the victim. There are two critical challenges for incurring the maximum delay to a victim—synchronization and adaptive attack, which we explain respectively as follows:

- *Synchronization.* In order for the adversary to incur the maximum delay under a resource constraint, it has to be able to (1) determine whether the victim process is running, and (2) predict the resource request from the victim process at a given time.
- *Adaptive Attack.* Based on the result of synchronization, the adversary should *align* its resource request (i.e., attack) with the victim. In general, the higher demand the victim has at a given time, the larger request the adversary should submit to the shared resource.

In the following, we shall describe our main ideas for addressing the two challenges respectively. Note that we focus on the synchronization and attack phases in this section, and discuss the design of the co-location phase in Section 3. Readers who are interested in the Swiper for a multi-VM system may consult Appendix E, available in the online supplemental material.

4.1 Main Ideas for Synchronization

In this paper we consider a simple adversarial strategy of conducting an *observation process* with a *sequential read* operation. We chose read over write because the time-series of throughput allocated to write operations tend to have sharp bursts, which would make the synchronization significantly more difficult. Both sequential and random reads in our tests yield similar results in terms of the accuracy of synchronization. We chose sequential read over random read because the latter is rarely the behavior of a normal user and therefore may be detected by the cloud computing system.

Before describing the details for synchronization, we first introduce a few basic notions: Recall that the adversary

holds as prior knowledge of the I/O request time series from the victim (when no other process is running). Let $v(t)$ be the bandwidth requested by the victim at t seconds after the victim starts running. At runtime, let t_{ob} (seconds) be the length of the observation process (where ob stands for *ob*servation length) and $a(t)$ ($t \in [1, ob]$) be the (observed) throughput allocated to the adversary for the tth second since the observation process starts. Let a_{U} be the (upper bound on) throughput for the sequential read operation when no other process is running.

The objective of synchronization is for the adversary to align the pre-known $v(t)$ with the observed time-series $a_{\text{U}} - a(t)$. In the ideal case, $a_{\text{U}} - a(t)$ would be a concatenation of two sub series: one with zero readings (i.e., when the victim has not yet started running or has finished running), and a sub-sequence of $v(t)$. In practice, however, additive noise and rescaling on both time and throughput may be applied, leading to a requirement on aligning $v(t)$ with $a_{\text{U}} - a(t)$ with *offset*, *stretching*, and *scaling* factors. Appendix C, available in the online supplemental material, provides the complete definition of these three factors, and Appendix D, available in the online supplemental material, explains our main theory for addressing the challenge of synchronization.

4.2 Performance Attack

Based on the result of synchronization, we consider a performance attack which launches multiple segments of sequential read operations to delay the victim process. Each segment persists for a fixed, pre-determined, amount of time. In the following, we discuss three critical issues related to the design of such a performance attack: (1) when should each segment be launched, (2) how long should each segment persist, and (3) why should each segment use a sequential read operation.

Positioning of attack segments. To incur the maximum delay to the victim process, the attack segments should be positioned to cover the moments of *peak* requests from the victim process. Thus, to position h attack segments each persisting for ℓ seconds, we use a greedy algorithm which first locates the ℓ-second interval in $v(t)$ which has not yet been executed and has the maximum total request, i.e., finds the start of interval $t_{\text{S}} \in [ob - t_{\text{off}}, N - 1]$ such that

$$t_{\text{S}} = \arg\max_{t} \sum_{i=t}^{t+\ell} v(i), \tag{1}$$

and then repeat this process after removing interval $[t_{\text{S}}, t_{\text{S}} + \ell]$ from consideration, until all h intervals are found. Note that there must be $t_{\text{S}} \geq ob - t_{\text{off}}$ because by the end of the observation process, the first $ob - t_{\text{off}}$ seconds of the victim process have already passed and thus cannot be attacked.

Length of attack segments. Somewhat surprisingly, our experiments (as we shall present in Section 6) show that as long as each attack segment covers a peak of the victim's request, the length of the attack segment does *not* have a significant impact on the delay incurred to the victim process. Intuitively, this is because the length of the attack which does not overlap with the peaks of victim's request incurs little delay to the victim. Nonetheless, this does not mean that the adversary should set each attack segment to be as short as possible—Instead, it has to take into account the estimation error of synchronization, and make the attack segment long enough to ensure the coverage of the peaks.

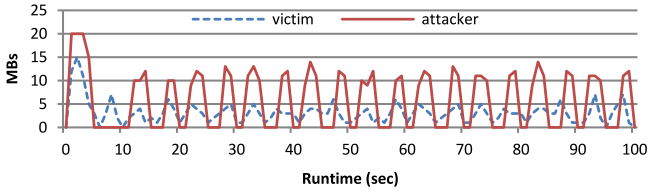


Fig. 1. Overlapping I/O of an attacker and a victim.

Operations of attack segments. Each attack segment may perform four types of operations: sequential read, random read, sequential write, and random write. We choose the sequential read operation due to the following reasons. First, we excluded the write operations from consideration for the same reason as that discussed for the design of the observation process: write operations tend to introduce sharp bursts on throughput, which makes it difficult to be synchronized with the victim's peak requests. We chose sequential read over random read because a random read operation is unlikely to sustain a high throughput to "compete" with the victim process and delay it.

One note of caution is that, while each attack segment should perform a sequential read operation, the adversary must ensure that consecutive (but different) attack segments do *not* read sequentially on adjacent blocks. This is because the hard drive or operating system may pre-fetch the latter blocks while performing the previous attack segment. As a result, the latter attack segment does not actually incur any I/O to the hard drive, incurring no delay on the victim process. To address this issue, a simple attack strategy is for each segment to first randomly choose one from a set of files, and then read the file sequentially.

Fig. 1 shows an example trace when Swiper issues overlapping sequential read operations to slowdown an co-located FileServer. When comparing Fig. 1 with the unaffected trace, we found Swiper issues most I/O operations when victim issues as well. In addition, victim's trace has been obviously distorted to certain degree. We will further analyze the performance decreases in Section 6.

5 Practical Issues in Running Swiper

We have established a framework to locate and interfere with target VMs, including a theory for synchronizing I/O patterns. There are critical issues that need to be addressed when deploying Swiper in real-world. We explicitly discuss two important factors in this section. First, some applications' activities depend on user inputs. Thus, we talk about how to deal with such non-determinism in Section 5.1. Second, migration is an important feature for virtualized systems to manage resources. Co-locating the target and attacker is critical in the proposed method. Since the target VM could be migrated thereafter, we discuss migration in Section 5.2.

5.1 Non-Deterministic User Behavior

Some applications' activities, e.g., Twitter and Wikipedia, are generated by users. Although one person may not

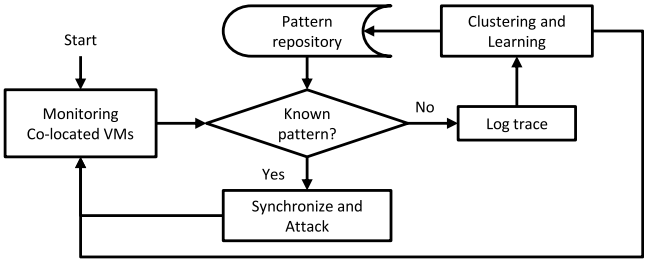


Fig. 2. An extended Swiper architecture for dealing with non-deterministic workloads.

repeat the same behavior hour after hour and day after day, a recent study on a Twitter trace revealed that aggregate workload demonstrates much more predicable I/O activities than single user's, i.e., similar aggregate I/O activities in one hour may occur at the same hour tomorrow and next week [30]. A previous analysis on long-term traces from Amazon web services and Google App Engine also found yearly and daily patterns [31].

Although historical traces could help in predicting I/O behaviors, self-learning and adaptivity to new I/O patterns are still good to have in a fast-changing world. Swiper can be easily extended to deal with non-deterministic workloads by integrating with a pattern repository and learning module. Fig. 2 demonstrates a high level sample architecture of an extended Swiper.

With this extended design, Swiper can adjust various parameters, e.g., the stretching factor, and capture more patterns to improve its success rate. We examine Swiper with non-deterministic workloads in Section 6.2. Note that designing clustering and learning methods for Swiper may by itself a new research topic. Thus we leave them as future works.

5.2 VM Migration

While live migration is a possible method of mitigating the interference from co-located workloads without service interruption, it does not come without a price. Indeed, previous work have shown that the performance may be substantially affected during migration [32], [33], [34]. For I/O-intensive applications in particular, since data can be stored or cached on high performance local storage to reduce the access latency, VM migration can be even more costly—lasting several minutes to hours depending on the size of VM virtual storage that is stored locally.

Alternatively, a practical method for reducing the migration time is to only migrate the computing instance (CPU and memory states) and keep VMs virtual disks on networked storage. For such setting, our experiments in Section 6.3 show that it is possible for Swiper to locate and impede the target VM again. In this case, a critical problem for the adversary is the cost because now the attacker needs to launch a number of probing VMs to search for the target after the VM migration. Note that this cost can be minimal in the cases that the adversary already held many hacked user accounts, which had happened before—e.g., in [35].

6 Experiment Results

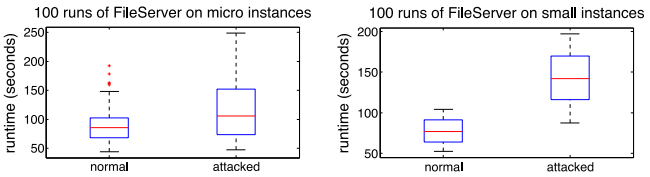
Because a substantial portion of Amazon EC2's address space hosts publicly accessible web servers [6], we test Swiper with the following popular cloud applications or benchmarks: Yahoo! Cloud Serving Benchmark **(YCSB)** is a performance measurement framework for cloud data serving [36]. YCSB's core workload C is used to emulate read-intensive applications; **Wiki-1** and **Wiki-2** are running Wikibench [37] with real Wikipedia request traces on the first day of September and October 2007 respectively; **Darwin** is an open source version of Apple's QuickTime media streaming server; **FileServer** mimics a typical workload on a file system, which consists of a variety of operations (e.g., create, read, write, delete) on a directory tree; **VideoServer** emulates a video server, which actively serves videos to a number of client threads and uses one thread to write new videos to replace obsolete videos; **webServer** mostly performs read operations on a number of webpages, and appends to a log file. The FileServer, VideoServer and webserver belong to the FileBench suite [38]. Micro and small Amazon EC2 instances and a local machine are used as the test platforms in this work. We use technique described in Section 3 to locate Amazon EC2 instances, which dwell in the same storage device. The tests are repeated for 50 times and the means are reported.

To evaluate the effectiveness of an attack, we define three metrics: 1) the slowdown/decrease in percentage of the victim, S, which assesses the overall effect of an attack. This can be measured as the runtime in seconds or the throughput in KB. 2) the victim slowdown divided by the total runtime (in seconds) of the attacker, S_{AT}, which determines the impact of the length of an attack. A bigger S_{AT} indicates that an attacker can infiltrate large damages within a shorter time window. 3) the victim slowdown divided by the total throughput (in MB) of the attacker, S_{AC}, which evaluates the effect of the bandwidth consumption of an attacker. A bigger S_{AC} means that an attack is effective while consuming a smaller amount of bytes.

6.1 Comparison with Baseline Attacks

Amazon EC2 instances. We first demonstrate our tests on Amazon EC2. To minimize cache effect and max out the bandwidth, we make the total file size of all four benchmarks larger than double of the memory size. Namely, the working set size of each benchmark is 4 GB on the micro and 8 GB on the small instance in this experiment. Fig. 16 in Appendix H, available in the online supplemental material, shows runtime increases of benchmarks on micro and small instances when the attacker is restricted with 2 and 4 GB data limit to interfere with the victim on the micro and small instance respectively.

Recall that naive attack exhausts the bandwidth within the given time or data constraints and random attack launches I/O requests at stochastic time points. The naive attack shows little to none effect on runtime increase of the victim workload. The average runtime increases caused by the naive attack are 6 and 14 percent on micro and small instance respectively. The random attack is better than the naive one because there are chances for the random attack to hit the peak of the victim workload. The random attack increases victims' runtime by 35 and 57 percent on micro and small instance respectively. The peak attack has the best results, which are 67 and 100 percent on micro and



(a) micro instance (b) small instance

Fig. 3. Boxplot of FileServer runtime by peak attack on micro and small instances.

small instance respectively. In general, micro instance is better than small instance in resisting attacks, which implies the networked disk array and storage duplicates help to reduce I/O interference. Despite the possible methods for mitigating the disk I/O interference, other shared system components are also susceptible to the interference issues, e.g., caches [28] and network interfaces [39]. The idea of Swiper could be complemented by combining with other techniques to exploit vulnerable components. As we shall see later, our method can effectively detect the I/O peak and launch workload to slowdown the victim. Altogether, the average runtime increase of peak attacks across instance types and benchmarks is 85 percent, about twice or eight times more than a random or naive attack, respectively.

Fig. 17 in Appendix H, available in the online supplemental material, shows victim's performance changes when varying attacker's data consumption limit. The peak attack still has the best result under different data usage limits. Note that instance store is more vulnerable than EBS and accessing instance stores has no extra cost for the adversary. An EC2 user should use EBS volumes instead of instance stores to reduce potential damage.

A boxplot of runtime reveals more insight on how peak attacks affect victims' performance. Fig. 3 demonstrates FileServer runtime distributions when peak attacks happen on micro/small instances. On the result of micro instances, peak attacks effectively change the distribution of runtime. The distribution now is skewed to higher values. On the result of small instances, almost all test results under peak attacks have longer runtime than normal runs. These two figures show that peak attacks can effectively slowdown a victim most of the times. Note that Amazon EC2 should be considered as a multi-VM testing environment because it is very likely that instances from other users are co-located.

The runtime increase may not provide a tangible idea on the monetary loss. Section 6.4 transforms the runtime increase into the revenue loss in business. Our analysis shows a significant amount of financial loss could be done by Swiper if the target is providing critical business services.

Two VMs. For conveniently analyzing different virtualization systems, we conduct the following tests on local machines with a 2.93 GHz Intel Core2 Duo E7500 processor, 4 GB RAM, and 1 TB Samsung hard drive. The host operating system is CentOS Linux with 2.6 kernel. Two paravirtualization frameworks are tested on this machine: One is the KVM and another is Xen 4.0. Note that Amazon EC2 also uses Xen. All VMs in the experiments have one VCPU and 512 MB memory.

The effectiveness metrics of three selected applications are shown in Table 1. The attacker's data usage is limited at 500 MB. The proposed peak attack clearly captures I/O request patterns and achieves additional performance degradation on both Xen and KVM. Peak attack generates an average S of 26.11 percent of the victim, compared to 6.25 and 6.67 percent from the naive and random attacks. Recall that S_{AT} is calculated as S divided by the total runtime (in seconds) of the attacker, and S_{AC} is S divided by the total data usage (in MB) by the attacker. For the peak attack, the normalized S by time and data usage are even better—the S_{AT} value is about 4.17 and 5.96 times better than those of the random and naive attacks, while S_{AC} is about 4.57 and 5.33 times better. The bar graphs of Table 1 are presented as Figs. 18, 19, and 20 in Appendix H, available in the online supplemental material, to illustrate the differences visually.

TABLE 1
S, S_{AT}, and S_{AC} of Xen/KVM in Two-VM Experiments

Application	Metric	Naive	Random	Peak
WebServer	S	7.06/4.37	6.74/1.70	22.70/26.07
	S_{AT}	0.75/0.53	0.72/0.29	3.81/3.62
	S_{AC}	0.014/0.008	0.015/0.003	0.048/0.084
Darwin	S	5.32/4.59	9.45/5.82	28.62/29.33
	S_{AT}	0.45/0.43	1.66/0.55	5.70/4.81
	S_{AC}	0.010/0.009	0.019/0.011	0.059/0.069
Wiki-2	S	6.59/9.60	8.41/7.59	24.69/25.27
	S_{AT}	0.72/1.01	0.89/1.48	2.88/2.45
	S_{AC}	0.013/0.019	0.017/0.017	0.068/0.054

We also study the I/O throughput degradation when the peak attack has different data usage limit. Fig. 4 illustrates the average throughout decreases of different applications running in a Xen VM when the peak attack has data usage limits at 100, 300, and 500 MB respectively. For every increase in the attacker's data consumption limit, victims will see a larger drop in throughput. Darwin is the most susceptible application among the whole testing benchmarks because of its intensive and clear read request patterns. The average throughput decreases are 4.57, 14.65, and 22.54 percent at 100, 300, and 500 MB data usage limit respectively.

Multiple VMs. In addition to the victim and attacker VMs, other VMs may co-exist as background processes. A cloud service can also be provided by collaborating more than one VMs. For example, one VM serves as the frontend portal and another VM is responsible for providing requested data. Therefore, applications in the following tests are composed of multiple VMs to construct a real world scenario. Recall that Wiki-1 and Wiki-2 are running Wikibench with traces from Wikipedia. Fig. 5 presents the changes in the I/O throughput of four cloud service systems. The results show that Xen and KVM are both vulnerable to this threat and none of them is clearly better in resisting it.

In Table 2, we present the effectiveness of three attack types on web serving applications when attacker's data consumption is limited at 500 MB. For the peak attack, the

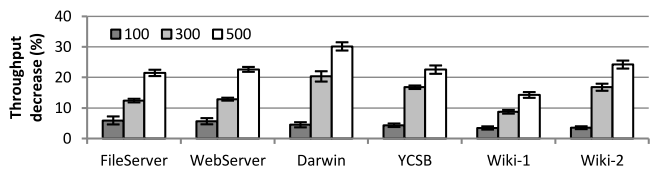


Fig. 4. The means and standard deviations of I/O throughput decreases.

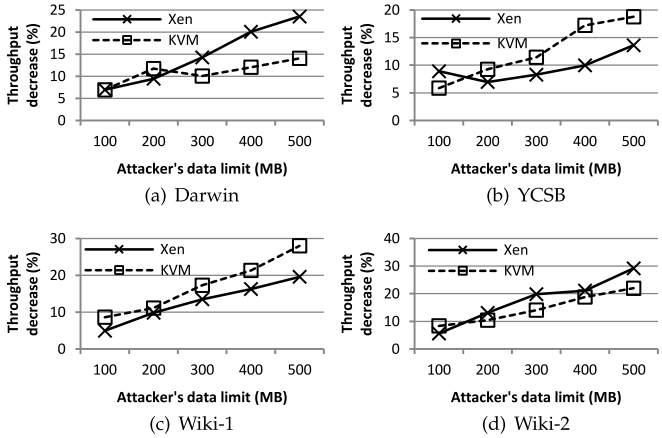


Fig. 5. Throughput changes when a multi-VM system hosted by Xen/KVM is attacked by the peak attack with various data usage limits.

normalized degradation by time and data usage are even better—the S_{AT} value is about 8.18 and 3.06 times better than those of the random and naive attacks, while S_{AC} is about 8.69 and 4.0 times better than those of the random and naive attacks. As Table 1, the bar graphs of Table 2 are also presented as Figs. 21, 22, and 23 in Appendix H, available in the online supplemental material, to illustrate the differences visually.

Note that Appendix E, available in the online supplemental material, has shown that attackers may need a longer observation length to maintain the synchronization accuracy when the number of VMs increases. Please refer to Appendix G, available in the online supplemental material, for the analysis of synchronization accuracy and Appendix H, available in the online supplemental material, for additional experiment results.

6.2 Dealing with Non-Determinism

This section demonstrates how Swiper works as a pattern detection method with a repository of collected patterns to cope with user randomness (see Fig. 2). The results and analyses indicate that Swiper could help in accomplishing an automatic attacking framework. As a prototype implementation, the pattern store consists of prestored 120 one-minute Wikipedia traces which are from 9 to 11 am on the 1st of October, Monday, 2007. Then, we replay a 24-hour trace on the same day to evaluate how Swiper reacts to the trace. Note the pattern here is the time and amount of bandwidth usage by the target. Since

TABLE 2
S, S_{AT}, and S_{AC} of Xen/KVM in Multi-VM Experiments

Application	Metric	Naive	Random	Peak
WebServer	S	9.47/6.82	1.45/2.29	29.5/12.23
	S_{AT}	0.85/1.15	0.20/0.31	2.76/2.10
	S_{AC}	0.018/0.013	0.003/0.005	0.073/0.030
Wiki-1	S	7.37/8.99	4.94/1.56	16.22/28.56
	S_{AT}	1.14/1.05	0.61/0.29	1.41/4.59
	S_{AC}	0.014/0.017	0.011/0.003	0.050/0.070
Wiki-2	S	6.26/7.83	4.70/3.20	26.51/23.73
	S_{AT}	0.95/0.77	0.39/0.40	4.99/2.31
	S_{AC}	0.012/0.015	0.010/0.006	0.080/0.054

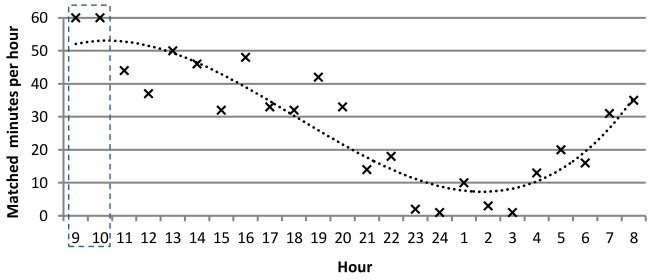


Fig. 6. Matched minutes at each testing hour in the one-day test when holding a two-hour traces in the repository. The dotted line shows a polynomial fit of the observed data points. The dotted rectangle shows the period for the training set.

we do not use any advanced pattern learning module (which by itself may become a separate research topic), we relax the scaling and stretching factors by 10 percent to allow Swiper to accept similar patterns in the 24-hour testing set. If there are more than one matched patterns due to the relaxation, the one with the least distortion will be selected. When Swiper identifies a known pattern in a one-minute interval, it will synchronize with and attack the victim during the remaining time of the matched minute. We limit the data usage of Swiper at 1 GB per matched minute. The machine setting of this experiment is the same as the two-VM one.

In Fig. 6, we first show the matched and attacked minutes at every testing hour during the experiment. This evaluation essentially shows how many one-minute traces are similar to the I/O patterns in the repository. The polynomial fit of the matched minutes shows a trend that similar patterns demonstrate time locality, which supports the findings in [30]. The requests during the night time (hour 12 to 20) are less frequent and intense and thus less similar to the stored patterns, which are from day time. Note that Swiper is looking for the similarity in I/O patterns. The request traces could be accessing different files but the disk could show similar reading patterns.

Because the extended Swiper relaxes the matching criterion and does not hold a full trace, attacking one matched minute does not necessary mean a correct match and guarantee a significant degradation as before. Therefore, Fig. 7 examines the average throughput decrease per attack at each testing hour.

Although the last 22 hours are not as good as the first two, the results confirm that a historical trace could still be useful in the future. The throughput degradation ranges from 2 to 20 percent and has an overall average of 13.12 percent. As future work, using clustering methods to

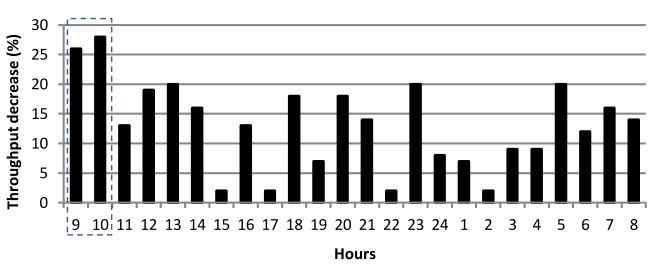


Fig. 7. The average throughput decrease per attack at each testing hour. The dotted rectangle shows the period for the training set.

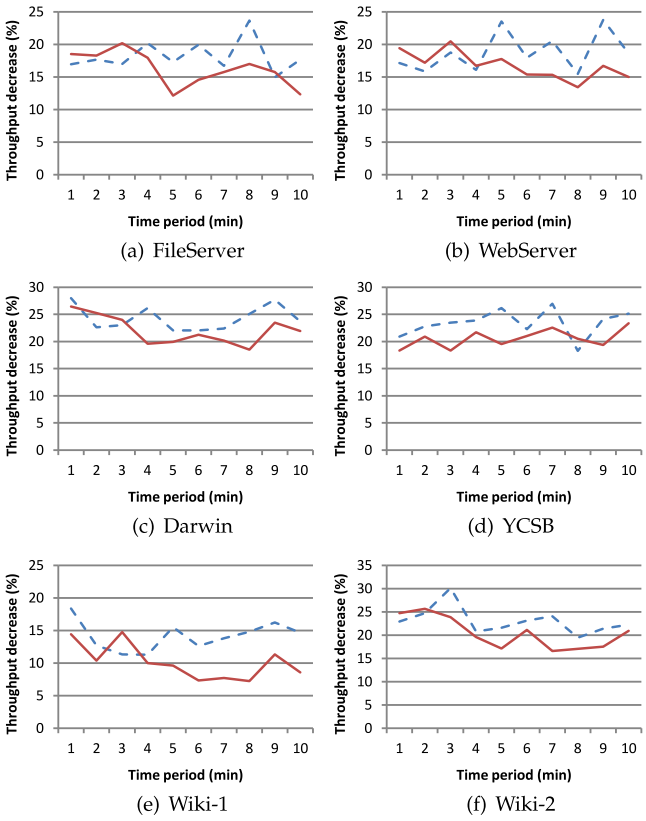


Fig. 8. The throughput decreases when the migration is enable are shown in red solid lines. The blue dotted lines represent the throughput decreases when the victim is not migrated.

identify and generate patterns may greatly improve the effectiveness of Swiper.

6.3 Attacking Migratable VMs

Live migration is a method that can be potentially used to reduce workload interference. In this section we run two experiments to study if live migration affects the attack and by how much.

In the first experiment, we assume the victim VM is aware of being attacked, and wants to be migrated away. The host machines, M_A and M_B, have an identical configuration and are the same as the one used in the previous two-VM tests. Hosts are interconnected on a Gigabit Ethernet, and share the same storage device on another machine M_C. Note that using the same VM image is a common practice because moving the disk image can vastly increase the pausing time of VM execution. The testing time of each run is 10 minutes, and the data usage of Swiper is limited at 500 MB per minute. In the first run, the attacker and the victim are both on M_A and the victim is attacked for 10 minutes. Then, in the second run, the victim is migrated away after being attacked for 2 minutes, but the attacker keeps interfering the storage accesses. Most of the migration times are less than a minute. Fig. 8 shows the average throughput decreases of these two scenarios in every testing minute. Note that the performance degradation after migration comes from the interference on a shared storage. The degradation is smaller by about 3.23 percent on average after migration because the short pausing time for migration makes I/O patterns shifted.

In the second experiment, the attacker will chase the target if it migrates away. We have four machines as VM hosts in this experiment. Each machine has two six-core Intel Xeon CPUs at 2 GHz, 32 GB memory, and 128 GB SSD. All VM images are stored on a storage node with two six-core Intel Xeon CPUs at 2.67 GHz, 24 GB memory, and 2 TB RAID0. Each VM has 1 VCPU and 2 GB memory. Every machine runs two background VMs, which randomly read and write multiple files. We start the target VM on one of the hosts. Then, we launch probing VMs to search, synchronize, and attack the target VM. We assume the target is aware of being attacked after 2 minutes. Then, it runs away to another host. After knowing the target is away, Swiper starts to looking for the target again. We repeat the same process for 20 minutes and for each testing application. Then, we conduct the same tests in a different scenario which does not allow migration. Fig. 24 in Appendix H, available in the online supplemental material, shows the average throughput decreases of these two scenarios in every testing minute. Almost every migration takes less than one minute. Each relocating process takes about 70 to 160 seconds, from being aware of losing the target to start attacking again. During these periods, the target VM still gets performance degradation because it pauses running for a short period of time and may still gradually copies memory pages from the previous machine until all dirty pages are synchronized, e.g., in the seventh minute of Fig. 24a and almost every migration in Fig. 24d, because of high dirty page rate, available bandwidth, or migration overheads [32]. On average, the adversary still hurts the targets performance by 16.32 percent even after the target tries to migrate and avoid the attacker.

6.4 Potential Monetary Loss

The runtime increase may not give a tangible idea on the monetary loss. Thus, we use a linear model to translate the runtime increase into revenue loss in business.

In Section 1, we have seen that 100 ms delay in loading pages may causes 1 percent revenue loss and 500 ms delay in displaying search results may reduce revenue by 20 percent. We also know that the median webpage loading time is about 3 seconds [40] and the average time to display the search result is 0.2 seconds [41]. We use these data as two linear cost versus delay models. Let's call them SLA1 and SLA2 cost models respectively. In case SLA1 and SLA2 models are too optimistic for Swiper, we also use SLA3 and SLA4 models which assume the expected loss is only one tenth of the SLA1 and SLA2 respectively. Then, the potential revenue loss caused by Swiper is interpolated from these models and our experiments on EC2.

The columns in Fig. 9 represent the potential revenue loss caused by the average runtime increase. The whisker lines represent the revenue loss caused by the minimum and maximum runtime increases from the experiments on EC2. The average revenue loss could be at least around 10 percent and up to 30 percent on small and micro instances when using SLA1 and SLA2 models respectively. Even with the SLA3 and SLA4, the average revenue loss is about 1.8 percent across two instance types and cost models, which is big enough to justify the co-locating cost of Swiper.

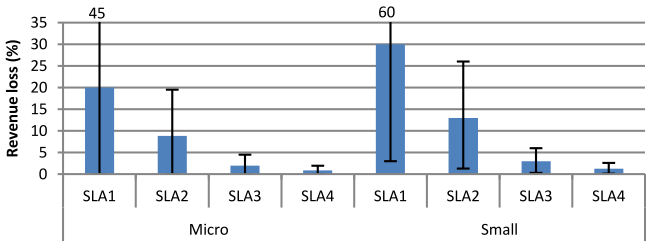


Fig. 9. Potential revenue loss caused by Swiper on small and micro instances.

Note that not all probing instances were running during the whole probing period. An instance is terminated immediately after confirming that there is no co-located target. Thus, the cost (data and instance usage) of probing and locking-on is small. For example, using micro (0.02 dollars per hour) and small instances (0.06 dollars per hour) as the probing VMs cost about one and three dollars for co-locating one target (based on the 2 percent success rate) respectively. Such initial cost is very small compared with the potential revenue loss shown in Fig. 9.

7 Conclusion

In this paper, we presented a novel I/O workload based performance attack which uses a carefully designed workload to incur significant delay on a targeted application running in a separate VM but on the same physical system. Such a performance attack poses an especially serious threat to data-intensive applications which require a large number of I/O requests. Performance degradation directly increases the cost of per workload completed in cloud-computing systems. Our experiment results demonstrated the effectiveness of our attack on different types of victim workloads in real-world systems with various number of VMs. Interested readers may refer to Appendix I, available in the online supplemental material, for the literature review and more discussions, where we have proposed a number of possible solutions to these types of attacks as future work. Also, it would interested to study the effects of system parameters, e.g., I/O schedulers and buffer sizes, on defending such attacks.

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