EIPSim: Secure IP Address Allocation at Cloud Scale

Abstract—**Public clouds provide impressive capability through resource sharing. However, recent works have shown that the reuse of IP addresses can allow adversaries to exploit the latent configurations left by previous tenants. In this work, we perform a comprehensive analysis of the effect of cloud IP address allocation on exploitation of latent configuration. We first develop a statistical model of cloud tenant behavior and latent configuration based on literature and deployed systems. Through these, we analyze IP allocation policies under existing and novel threat models. Our resulting framework, EIPSim, simulates our models in representative public cloud scenarios, evaluating adversarial objectives against pool policies. In response to our stronger proposed threat model, we also propose *IP scan segmentation*, an IP allocation policy that protects the IP pool against adversarial scanning even when an adversary is not limited by number of cloud tenants. Our evaluation shows that IP scan segmentation reduces latent configuration exploitability by $500\times$ over the IP allocation policies deployed be cloud providers, compared to $14.5\times$ for prior explored techniques. Finally, we evaluate our statistical assumptions by analyzing real allocation and configuration data, showing that results generalize to deployed cloud workloads. In this way, we show that principled analysis of cloud IP address allocation can lead to substantial security gains for tenants and their users.**

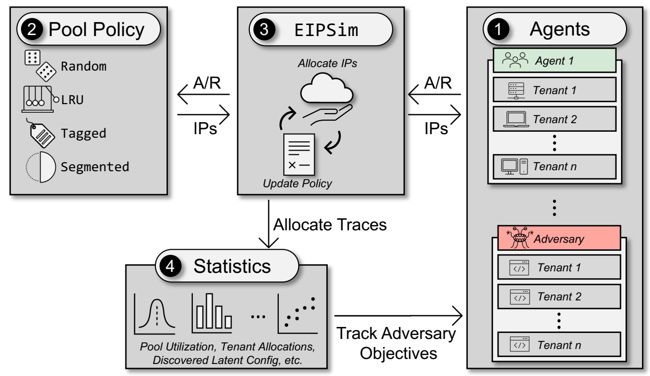


Figure 1: Overview of our analysis - ❶ We first define agents who (A)llocate and (R)elease IP addresses in varying modalities (including adversarial behaviors), ❷ we then evaluate a suite of IP pool allocation policies that govern IPs associated with tenants, ❸ we then simulate interactions between agents and policies, and ❹ collect various statistics concerning pool utilization, adversarial goals, etc.

1. Introduction

Cloud providers allow near limitless scalability to tenants while reducing or eliminating upfront costs. One component that enables this architecture is the reuse of scarce IPv4 addresses across tenants as services scale. Recent works [1], [2], [3], however, have shown that this practice exposes new security risks as malicious tenants exploit *latent configuration* created by prior users of an address. Thus, cloud providers are motivated to manage their IP space such that adversaries cannot easily discover a large number of IP addresses and exploit prior tenants.

A promising approach proposed in prior work [2] is to use disjoint IP address pools between tenants, reducing the IPs exposed to adversaries. While subsequent work has proposed approaches towards this [3], the community still lacks a complete understanding of the security provided by these measures, especially against a more powerful or adaptive adversary. For instance, an adversary that can leverage many cloud accounts defeats the protections of prior works. Further analysis of IP allocation policies could establish shortcomings under these new threat models, and motivate new defenses that more effectively protect the IP address pool.

In this paper, we present the Elastic IP Simulator (EIPSim), a comprehensive framework for evaluating the security of cloud IP address allocation. Shown in Figure 1, EIPSim models a set of IP allocation policies, tenant behaviors, and adversaries that adapt to deployed policies and attempt to maximize exploited addresses. Our tool can be used to generate representative simulations of public clouds, or traces from real-world cloud providers can be used to precisely characterize a given environment. Our performance evaluation demonstrates that such a simulation can be performed at the scale of major cloud providers while incurring acceptable execution time cost (e.g., simulating a zone of Amazon Web Services at $58000\times$ realtime speed). In addition, our flexible architecture allows fair comparison with future developments in secure IP allocation.

Within our simulation, we test both state-of-the-art (e.g., auto-scaling) and novel models for tenant allocation behavior, IP allocation policies, and adversarial approaches. We develop a set of tenant agents that simulate representative workloads (i.e., inspired by analysis of real tenant behavior) deployed by tenants. IP allocation policies discussed in prior works are modeled, and we create new models for how adversaries would adapt to these techniques to continue gaining coverage of the IP address pool. In response to these adaptive adversaries, and based on our simulations of their effectiveness, we then propose *IP scan segmentation*, a novel IP allocation policy that heuristically identifies adversarial behavior across many cloud tenants and effectively segments the pool to prevent such adversaries from exploiting vulnerabilities.

We use EIPSim to evaluate the security properties (adversarial ability to discover unique IPs and latent configuration) of our studied allocation policies and tenant/adversarial behaviors in settings representative of real cloud settings. This highlights the performance improvements of our proposed techniques, demonstrating that IP allocation policies can have a marked impact on the exploitability of vulnerabilities caused by IP address reuse. Indeed, our analysis shows that IP scan segmentation reduces adversarial success by $500\times$ over the IP allocation policies deployed be cloud providers, compared to $14.5\times$ for prior explored techniques. We further evaluate our model assumptions against real-world allocation traces, and by analyzing the distribution of latent configuration from an existing measurement study [3]. We release our simulator as open source software so that cloud providers can analyze their tenant behavior and evaluate appropriate steps towards protecting users. In this way, we show that principled study of IP address allocation can lead to practical security improvement for public clouds.

IP address reuse poses a practical security concern, but principled study of new allocation techniques can lead to substantial improvement towards making this reuse less exploitable in practice. Through our modeling and analysis, our work provides a basis on which future research in IP allocation can be measured.

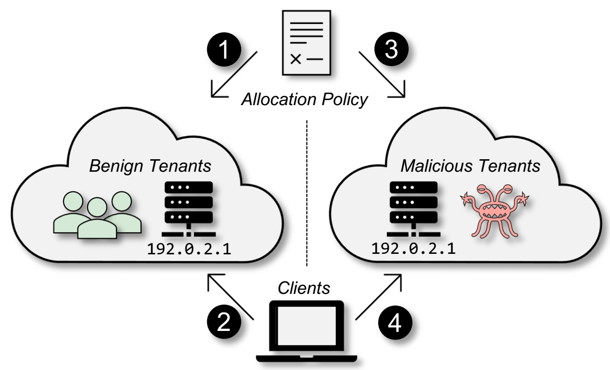


Figure 2: Exploiting IP Reuse - ❶ A benign tenant receives an IP address per an IP pool allocation policy, ❷ clients then connect to the service and establish a trust relationship with the IP address, ❸ after the benign tenants decommission the service (and thus release the associated IP), a malicious tenant is then granted the same IP address per the allocation policy, and ❹ the client then unknowingly connects with the decommissioned service now hosted by the adversary.

2. Background & Related Work

Our work addresses security properties of IP address allocation for public clouds. As such, we briefly describe considerations in IP allocation generally, as well as contemporary work in cloud security related to IP address allocation and configuration management.

2.1. IP Address Allocation

Network hosts require an IP address for communication. This can be manually assigned or managed out of band, or it can be provisioned through some automation. In home and corporate networks, the standard solution to automatic IP allocation is DHCP [4]. Likewise, in public clouds such as Amazon Web Services [5], Microsoft Azure [6] or Google Cloud [7], servers are allocated a private (i.e., RFC1918 [8]) IP address via DHCP [4]. While the DHCP standard does not specify how addresses are assigned, they are generally drawn from a pool either sequentially or based on the physical (MAC) address of the requesting machine [4]. For workloads with only private or outbound communications, these addresses are sufficient, as outbound connections can be mapped to publicly-routable IPs via Network Address Translation (NAT) [9].

When services need to receive connections from the broader Internet, they require a public IP address (usually, at a minimum, an IPv4, though support is increasing for IPv6 [10]). These addresses could be configured directly in the machine or over DHCP. However, cloud providers generally opt to use NAT [9] to route public IP addresses to the private IPs of servers. This has multiple benefits, including flexibility (public IPs can be changed dynamically without host involvement), security (tenants cannot spoof IPs), and ease of management (centralized view of IP address allocations).

Cloud Provider IP Allocation. When a tenant requests an IP address, cloud providers have a choice to return any unused address they control, subject to their own internal policy. For instance, a recent work [3] showed that Amazon Web Services samples their pool of available addresses pseudo-randomly subject to a 30-minute delay between reusing any given address. Another study [11] found that IP reuse followed a random process, though the ranges of used IP addresses could be inferred from many samples of the pool. Other works have found that Microsoft Azure [2] and Google Cloud Platform [12] show allocation behavior consistent with random allocation. While this random allocation can have the positive effect of allowing for a moving-target defense, wherein tenants move around the IP address pool to evade attack, it also leads to severe security weaknesses when configurations are mismanaged.

2.2. IP Reuse and Latent Configuration

Tenants use IP addresses to refer to resources hosted on cloud providers, causing clients to connect to the resources and establishing trust relationships. Recent works [1], [2], [3] have shown that, when tenants fail to remove the configurations referring to IP addresses they no longer control, these *latent* configurations can be exploited by future tenants, as shown in Figure 2. Clients continue to send sensitive data, which is often unencrypted due to trust in the network isolation of the cloud provider. Further, this vulnerability is relatively easy for adversaries to exploit *en masse* on popular cloud providers, as the rapid and random reuse of IP addresses leaves little time for organizations to correct latent configurations. This leaves a long *window of vulnerability* during which adversaries could identify and exploit latent configuration. The community has proposed methods for correcting configurations such that they do not become latent, but changes to IP address allocation can also play a role when tenants fail to take action.

Preventing exploitation of IP Reuse. Changes to IP allocation policies have been shown to reduce the exploitability of IP Reuse. The insight here is to make it more difficult for adversaries to allocate IP addresses with associated latent configuration, either by (1) reducing the total number of unique IPs an adversary can allocate [2], (2) increasing the time since an IP was last used by another tenant, and (3) reducing the total number of past tenants associated with IP addresses. Intuitively, these measures might reduce exploitability—indeed, one study [3] provides initial metrics suggesting that the techniques could work in practice. Yet, the community's understanding of the space of attacks and countermeasures here remains incomplete: the ways in which an adversary might adapt to new techniques have not yet been modeled, and resulting further improvements to IP allocation strategies have yet to be explored.

2.3. Configuration Management

Outsourcing to public cloud providers offers a means to efficiently meet the operational requirements of modern network services, but introduces challenges in managing service configurations. Prior work has demonstrated that configuration complexity may increase substantially with the scale of the service [13], [14] and from the added tasks associated with making services cloud native (i.e., using advanced features such as auto-scaling [15], [16]). Automated configuration management tools (such as Puppet [17], Chef [18], and Ansible [19]) have eased this complexity to some extent. Further, infrastructure-as-code (IaC) [20] tools (such as AWS CloudFormation [21] or Terraform [22]) have made configuration management almost entirely non-interactive. However, while automation tools can eliminate most human-errors at runtime, a large proportion of configuration errors have been attributed to subtle bugs in the configuration files themselves (or ambiguities in the code generating them) [14] and other improper lifecycle management practices [13] (e.g., failing to remove configurations pointing to released IPs [1]). Our work aims to provide recourse for cloud providers and tenants by: (1) allowing them to assess the degree to which tenants are vulnerable to latent configuration, and (2) informing best practices on IP allocation policies that mitigate these vulnerabilities.

3. Modeling the IP Address Pool

Here, we present a comprehensive framework for modeling secure IP address allocation. Towards this, we propose statistical models for tenant behavior (resource allocation and latent configuration), describe algorithms for allocation policies (including our propsed *IP Scan Segmentation* policy), and descriptions of the threat models under which adversaries might exploit cloud resources. In each case, our methodology is informed by prior works, and validated based on real-world allocation and configuration datasets. *Note:* a reference of symbols used throughout the paper can be found in Appendix A.

3.1. Tenant Behavior

Cloud providers lease resources (e.g., IPs) to tenants under two general paradigms: static and dynamic [23], [24], [25], [26], [27]. Static allocation allows tenants to acquire a specified amount of resources (perhaps for a fixed period of time); such resources are often used to handle workloads with known or predictable behavior. On the other hand, dynamic allocation allows tenants to acquire and release resources on-demand (to specified upper and lower limits); such resources are typically backed by auto-scalers and other automation tools to handle less predictable workloads efficiently [28]. As such, we model the behavior of tenants within a spectrum of potential allocation strategies (defined in terms of the number of IPs currently allocated to the tenant) spanning static and dynamic resource allocation.

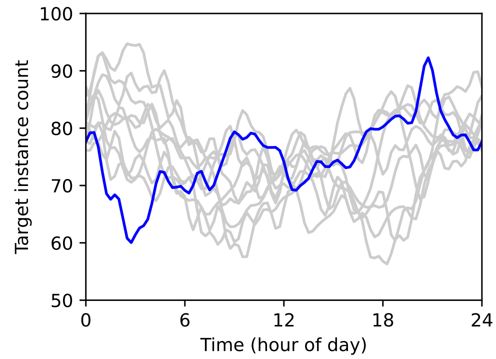


Figure 3: Example resource allocation traces based on Fourier series (with $S_{max} = 100, S_{min} = 50$). Each trace is individually realistic, and limiting $\phi_1 < 0.5$ leads to a realistic overall trend.

Benign tenants independently allocate IP addresses at some time t_a from the pool and release those addresses at a later time $t_r > t_a$ (here, the IP is said to be allocated for $d_a = t_r - t_a$). Tenants also associate configuration with IP addresses, which is dissociated from the IP at t_c. Each tenant's overall behavior B_i with respect to IP allocation can therefore be described as a set of timestamps:

$$B_i = \{(t_{a,0}, t_{r,0}, t_{c,0}), \ldots, (t_{a,n}, t_{r,n}, t_{c,n})\},$$

where n is the total number of IPs allocated to the tenant. A single tenant's behavior then has a maximum limit of S_{max} servers and minimum limit of S_{min} servers; this can capture both static ($S_{max} = S_{min}$) and dynamic ($S_{max} > S_{min}$) resource allocation. For the purposes of our experiments, we focus primarily on dynamic allocations using auto-scalers, as we found this to be most representative of cloud tenant workloads [28], [29].

We next model each tenant's behavior as being independently sampled from a distribution of potential tenant behaviors: $B_i \sim \mathcal{B}$. We approximate $\mathcal{B}$ as a randomized n-term Fourier series with a base period of one day [29]. The intuition is that a given tenant's resource needs will likely vary throughout the day as demand peaks and subsides, but for a given tenant, this pattern will likely be similar from day to day. One work [29] suggests modeling with a period of 1 week for more precision. Our framework is flexible in this regard, but simulations are performed with 1-day periods. Recall that, by the Shannon-Nyquist sampling theorem [30], *any* daily-periodic function can be approximated by a Fourier series of sufficient terms. We compute their current server utilization as a function of the current time t ($0 \leq t \leq 1$), where 0 and 1 represent the beginning and end of the day, respectively. We then model the mean server usage of the tenant ($\bar{S} = \frac{S_{max}+S_{min}}{2}$) and the relative deviation from the mean server usage using the Fourier series:

$$\frac{S(t)-\bar{S}}{S_{max}-S_{min}} = \frac{\sum_{i=1}^{n} \frac{a_i}{i} \sin(2\pi i(t+\phi_i))}{\sum_{i=1}^{n} \frac{a_i}{i}},$$

where the Fourier amplitudes (a_i) and phases (ϕ_i) are randomly sampled from the range $[0,1]$. This series has an expected range of $[-0.5, 0.5]$, spanning from S_{min} to S_{max} throughout a simulated day. The tenant then allocates or releases IP addresses to respond to this change in compute needs [31]. In keeping with the behavior of a major cloud provider [32], IP addresses allocated under autoscale behavior are selected at random for release when a tenant scales down infrastructure.

Modeling autoscaling behavior as a Fourier series creates traces of tenant allocation that are sufficiently realistic to simulate allocation policies (see Figure 3). However, on its own it fails to account for the fact that IP allocations in a given cloud provider region would likely be correlated (due to the local geographies served by that region [33]). We account for this by biasing the sampling of the lowest-frequency phase of the Fourier series (ϕ_1): enforcing that $\phi_1 < 0.5$, for instance, will roughly align peak loads to one half of the day. Moreover, tenants may have multiple workloads deployed under the same account that exhibit a hybrid of the above and other behaviors. While evaluation of these hybrid allocation behaviors is beyond the scope of this work, we note that EIPSIM can also be extended to support other models (or distributions) of tenant behavior, as well as real-world allocation traces. Analysis on real allocations (Section 5.8) are generally consistent with those based on Fourier-distributed allocations, though effectiveness could vary on other workloads.

3.2. Latent Configuration

As discussed above, tenants associate configuration with IP addresses when they are allocated. In most cases, this configuration is dissociated from the IP when or before the IP is released ($t_c \leq t_r$). In some cases, however, the configuration remains ($t_c > t_r$). If an adversary manages to allocate the IP address before t_c, we consider the adversary to have exploited the configuration. The time between IP release and latent configuration ($t_c - t_r$) is the *duration of vulnerability* d_v for a given tenant and IP.

Tenant behavior in dissociating configuration can be highly diverse. For feasibility, we model this configuration dissociation as a Poisson process. We assume that with some probability (p_c, a simulation parameter) the tenant leaves latent configuration. If latent configuration is left, it will be dissociated from the IP after some duration $d_v = t_c - t_r$. We model this as an exponential distribution

$$d_v \sim \text{Exponential}(1/d_a),$$

where the duration of vulnerability is distributed proportionally to the duration of allocation. Recall the probability density function of such a distribution:

$$f(d_v) = \begin{cases} \frac{1}{d_a} e^{-\frac{d_v}{d_a}} & d_v \geq 0 \\ 0 & d_v < 0 \end{cases}.$$

This distribution approximates the relationship between the duration of vulnerability and duration of allocation. It reflects empirical observations of cloud deployments [14], where relatively short-lived allocations are often orchestrated by automation tools and receive frequent configuration updates (and thus are less prone to having latent configurations), and relatively long-lived allocations are often configured manually and receive infrequent configuration updates (and thus are more prone to having latent configurations). In analysis of data on real-world latent configuration (Section 5.7), we find additional evidence supporting this distribution.

3.3. Adversarial Behavior

Within a public cloud, an adversary aims to obtain a large number of IP addresses with the goal of exploiting previous tenants. We proceed by describing the threat model and capabilities of such adversaries, following by two modes of behavior: single-tenant (proposed by a prior work [3] and multi-tenant (a new consideration of this work).

3.3.1. Threat Model

Our work considers an adversary attempting to scan a cloud provider's IP address pool to exploit latent configuration left by other tenants (as demonstrated in [2], [1], [2]. This adversary has no privileged access to cloud resources, and bypasses no security controls in place. Instead, they can only provision resources using paid cloud accounts on a platform. In addition, the adversary could perform a sybil attack, wherein they control a large number of cloud accounts that are indistinguishable from unique paid customers (e.g.,, by stealing credentials from other accounts). We parameterize adversaries by their compute budget (in unique IPs allocated simultaneously) and number of cloud accounts. These may not be a direct financial cost to an adversary who steals accounts or payment details, they do still represent an opportunity cost, as these credentials could be used for other profitable purposes. The goal of this work is to decrease the effectiveness and increase the cost of such an attack as much as possible.

Within our scenario, the adversary has the capability to allocate IP addresses through public cloud offerings (e.g., Amazon EC2). Because we assume the cloud provider cannot soundly determine which tenants are controlled by the adversary, it must serve all tenant requests that are within policy. For instance, allocating many instances and IP addresses is commonly used for autoscaling and short-lived tasks[29]. A cloud provider's actions must be a subset of those that would occur under existing offerings. For instance, while a cloud provider must allocate IPs to paying tenants, it may choose any free IP address to allocate. Based on this threat model, prior works [2], [3] have proposed a single-tenant adversary that allocates IPs under one tenant. This work considers a stronger adversary that has access to multiple tenants, defeating existing defenses.

3.3.2. Single-tenant Adversary

Discussed in prior works [1], [2], [3], a single-tenant adversary provisions IP addresses under a cloud account with the aim of finding addresses with latent configuration. In most cases, the most effective means by which to do this is to rent virtual servers with an associated IP address. A tenant allocates many of these servers simultaneously, runs them for the minimum time required to observe associated configuration, and then releases the IPs back to the provider (or retains the server if there is interesting configuration associated). In this way, the tenant can easily sample from the IP address space unless the provider takes steps to prevent it. In line with cloud provider service quotas on concurrent allocations [34], our simulated single-tenant adversary allocates up to 60 IPs simultaneously for 10 minutes each, before releasing the IPs and allocating new ones.

3.3.3. Multi-tenant Adversary

The multi-tenant adversary adapts to protective allocation policies by leveraging multiple tenants for allocations. An adversary could create multiple tenants using Virtual Private Networks and private credit cards to evade detection[1]. Under this threat model, we also assume that a cloud provider must make allocation decisions based solely on tenant behavior, and cannot identify collusion between tenants otherwise. Further, the cloud provider must prioritize availability, and so must grant tenant allocation requests even if they believe the tenant to be malicious. Due to these factors, the multi-tenant adversary represents a stronger threat model that existing allocation policies may not protect against. In the worst case (and as simulated in Section 5.5), the adversary would continually use new accounts after allocating the maximum concurrent IPs on a single account.

3.4. IP Allocation Policies

When tenants request an IP address from the cloud provider, the provider can choose which IP to assign to the tenant. Here, we assume (and prior works have shown [1]) that the cloud provider can freely choose to assign any free IP address within some zone to a tenant, and that there is no technical restriction on when IPs get reused. As noted (Section 2.1), cloud providers use NAT to route public IP addresses, so assignment of these addresses can happen instantaneously and without any restriction from the underlying network topology.

Within this framework, the policy is a stateful set of functions that ALLOCATE, RELEASE, and INIT IP addresses:

ALLOCATE$(T,\theta) \longrightarrow (ip,\theta')$: Accepts a tenant id T and an opaque state θ (for tracking IP allocation parameters) and returns a new, usable IP for the tenant, as well as an updated opaque state θ'.

RELEASE$(ip,\theta) \longrightarrow (\theta')$: Accepts an allocated ip (previously allocated by some tenant id T) and an opaque state θ and releases the IP back to the pool, returning an updated opaque state θ'.

INIT$(ip,\theta) \longrightarrow (\theta')$: Accepts a new ip into the pool that was never previously allocated, and returns an updated state θ'.

All calls to ALLOCATE and RELEASE are paired in order, such that IP addresses are in use by at most one tenant at a time.

We next describe different allocation policies considered in EIPSIM and provide their implementation in natural language and pseudocode. Note that if the RELEASE and INIT interfaces are not provided, it is assumed that the default implementations presented in Algorithm 1 are used. Of these policies, the RANDOM policy is implemented in practice by cloud providers [3], [2], and the LRU and TAGGED policies were proposed by a prior work [3]. In addition to these policies that encompass the current state of the art, we propose and evaluate a new policy, *IP scan segmentation*.

Function `RELEASE` (ip,θ) **:**
  $ip.t_r \leftarrow$ `currentTime`$()$;
  $\theta' \leftarrow$ `setIpNotAllocated`(θ, ip);
  return θ'
end
Function `INIT` (ip,θ) **:**
  $\theta' \leftarrow$ `createIp`(θ, ip);
  return θ'
end

Algorithm 1: Default RELEASE and INIT interfaces

3.4.1. Pseudorandom (RANDOM, Algorithm 2).

The most basic IP allocation policy (and that used by major cloud providers [11], [3]) is pseudorandom allocation. Here, IPs are sampled randomly from the pool of available addresses, with the only restriction that IPs cannot be used within d_{reuse} (30 min as observed on a major cloud provider). It has benefits for ease of use and understanding, as minimal information needs to be associated with the address. Further, the pool could be managed in a distributed fashion (such as within separate datacenters).

Function `RANDOM.ALLOCATE` (T,θ) **:**
  $ip \leftarrow$ `randomSample`$(\mathcal{I} \setminus \mathcal{I}_{A_t})$;
  while `currentTime`$() - ip.t_r < d_{reuse}$ **do**
    $ip \leftarrow$ `randomSample`$(\mathcal{I} \setminus \mathcal{I}_{A_t})$;
  end
  $\theta' \leftarrow$ `setIpAllocated`(θ, ip);
  return ip, θ'
end

Algorithm 2: (RANDOM) IP Allocation

3.4.2. Least Recently Used (LRU, Algorithm 3).

The LRU policy seeks to maximize the median time between reuse of IP addresses. It does this by always allocating the IP address that has been in the pool the longest. Such an algorithm can either be implemented deterministically (e.g., using a FIFO queue), or stochastically (e.g., by sampling a subset of the IPs in the pool and returning the oldest of that batch). Such stochastic approaches have been shown to achieve acceptable performance in practice for caches [35].

3.4.3. IP Tagging (TAGGED, Algorithm 4).

In a recent work, Pauley et al. [3] presented a novel IP allocation policy specifically intended to prevent adversaries from scanning the IP pool. Referred to as *IP Tagging*, the authors describe that, intuitively, released IP addresses are tagged with the tenant ID that released them. When allocating an IP, tenants first preference the IP addresses that they are tagged to, followed by

1. Note that our threat model assumes the adversary is still cost-limited, either directly or in ability to acquire usable stolen credit card numbers.

```
Function LRU.ALLOCATE (T,θ):
    ip ← argmin_{ip∈I\I_{A_t}} (ip.t_r);
    θ′ ← setIpAllocated(θ,ip);
    return ip,θ′
end
```

Algorithm 3: LRU IP Allocation

addresses tagged to any other tenant using LRU allocation. Our implementation additionally stipulates that tagged IP addresses are selected in an LRU fashion, though other variants such as selecting the most-recently-used tagged IP may also be valid approaches. In any case, selecting a tagged IP address inherently exposes no additional IP address or tenant configuration to an adversary. Our evaluation also further characterizes IP Tagging beyond the metrics performed in prior work to assess the generality of the technique to stronger adversaries.

```
Function TAGGED.ALLOCATE (T,θ):
    if ∃ip∈I\I_{A_t} | ip.ID=T then
        ip ← argmin_{ip∈I\I_{A_t}} (ip.t_r | ip.ID=T);
    else
        ip,_ ← LRU.ALLOCATE(T,θ);
    end
    ip.ID ← T;
    θ′ ← setIpAllocated(θ,ip);
    return ip,θ′
end
```

Algorithm 4: TAGGED IP Allocation

3.4.4. IP Scan Segmentation (Algorithm 5).

While IP tagging provides protection against a single-tenant adversary, the technique could be susceptible if an adversary spreads allocations across many tenants, bypassing the tagging entirely. In response to this threat, and our more powerful characterization of pool scanning adversaries (Section 3.3.3), we propose a new IP allocation policy that aims to prevent IP scanning by adversaries even when the adversary has access to an arbitrary number of cloud tenants.

Our proposed policy, *IP scan segmentation* (shown in Figure 4), works by identifying tenant behavior that is indicative of (and necessary for) IP pool scanning. The pool tracks the *mean allocation time* ($\bar{d_a}$) for each tenant T: relatively long-lived resources will lead to high $\bar{d_a}$, and adversarial scanning (which inherently must allocate many IPs) would require a low $\bar{d_a}$ to be economically feasible. IP addresses are tagged with both (a) the ID of the most recent tenant, and (b) the duration the IP was allocated for (this decays over time, see *cooldown time*). If the IP was previously held for longer, this value does not change (so that a short allocation does not delete the protection from a previous longer allocation).

When a tenant allocates an IP address, preference is first given to an IP tagged to that tenant (as in IP Tagging), followed by an IP from the pool that was previously allocated for as close as possible to $\bar{d_a}$. In this way, adversary tenants that scan the IP space will in turn be allocated IP addresses that were previously allocated for short periods of time, either by another adversary tenant or by tenants deploying short-lived workloads (which are less likely to have associated latent configuration).

Cooldown time. As noted above, each IP is tagged with the longest duration it has been held for. Over time, this approach alone would cause more and more IPs to be tagged with long duration, leaving fewer and fewer with short durations and eventually allowing scanners to allocate the IPs that should be protected. Due to the scarcity of IP addresses, granting every IP address high protection means no IP receives protection.

To prevent this, the SEGMENTED policy applies a cooldown to the allocation duration over time with rate $1/\alpha$. The duration associated with an IP is therefore $d_a - (t - t_r)/\alpha$. Rather than continually update this duration in data structures, the SEGMENTED policy tracks the x-intercept of this function. This intercept, the *cooldown time* of the IP, is the time when the IP will no longer be provided any protection by the SEGMENTED policy. To select the IP with the most similar allocation duration for a given tenant, the policy minimizes $|(t_{cd} - t) - \alpha \cdot \bar{d_a}|$. In this way, tenants receive IP addresses that have exhibited similar allocation behavior to their past allocation behavior. Additionally, new tenants start with $\bar{d_a} = 0$, so they will receive IPs that have been segmented for allocation to scanners.

Since adversarial scanning would require a low $\bar{d_a}$ to be economical, an adversary tenant would then be matched with IPs that were either released a long time ago or were kept for a very short amount of time, mitigating some of the risk of an adversary acquiring an IP with latent configuration. Further, IPs recently released by the adversary would have a t_{cd} consistent with their average allocation duration, increasing the likelihood that they receive the same IP back even under a different tenant.

4. Implementation

To empirically study the distribution of IP allocation behaviors, adversarial techniques, and cloud provider defenses, we develop an IP pool simulator (EIPSIM). EIPSIM is written in 1700 lines of Go, and implements an extensible and configurable architecture for simulating interactions with IP address pools. For tractability, EIPSIM's components are designed towards performance:

Agents implement benign or adversarial behavior across a set of tenants simultaneously. For instance, an auto-scale agent tracks the allocations of all auto-scale tenants, and initiates required allocations across tenants simultaneously. The adversarial agent manages all adversarial tenants together.

The Simulator accepts a policy and agents, and manages configuration parameters. The simulation operates in time steps (1 s for all current evaluations, but tunable as needed for scalability). At each time step, agents can allocate or release IPs, and requests are passed to the policy for processing. The simulator also tracks time-series and aggregate statistics for later analysis.

Additional implementation details are provided in Appendix A. EIPSIM and evaluation code is being made

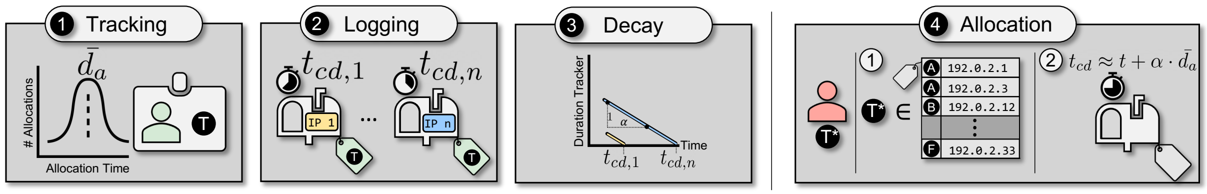


Figure 4: IP Scan Segmentation - ❶ The mean IP allocation duration for tenant T is tracked (i.e., $\bar{d}_a$), ❷ each released IP n is first associated (i.e., tagged) with tenant T & the allocated duration , ❸ the duration associated with the IP n then decays linearly with rate $1/\alpha$ (stored as the cooldown time t_{cd}), and ❹ when an IP is allocated for tenant T^*, preference is first given to a T^*-tagged IP, then to an IP from the general pool whose t_{cd} is closest to $t+\alpha\cdot\bar{d}_a$.

Function SEGMENTED.ALLOCATE (T,θ) **:**
  $T.n_a \leftarrow T.n_a + 1$;
  if $\exists ip \in \mathcal{I} \setminus \mathcal{I}_{A_t} \mid ip.ID = T$ **then**
    $ip \leftarrow \underset{ip \in \mathcal{I}\setminus\mathcal{I}_{A_t}}{\text{argmin}} (ip.t_r \mid ip.ID = T)$;
  else
    $ip \leftarrow \underset{ip \in \mathcal{I}\setminus\mathcal{I}_{A_t}}{\text{argmin}}(|ip.t_{cd} -$ currentTime() $- \alpha \cdot T.\bar{d}_a|)$;
  end
  $ip.ID \leftarrow T$;
  $ip.t_a \leftarrow$ currentTime();
  $\theta' \leftarrow$ setIpAllocated(θ, ip);
  return ip, θ'
end
Function SEGMENTED.RELEASE (ip,θ) **:**
  $ip.t_r \leftarrow$ currentTime();
  $ip.t_{cd} \leftarrow ip.t_r + \alpha \cdot (ip.t_r - ip.t_a)$;
  $T \leftarrow ip.ID$;
  $T.d_a \leftarrow T.d_a + ip.t_r - ip.t_a$;
  $\theta' \leftarrow$ setIpNotAllocated(θ, ip);
  return θ'
end

Algorithm 5: SEGMENTED IP Allocation

available as open source paper artifacts for researchers and cloud providers to improve offerings.

5. Evaluation

We proceed by evaluating EIPSIM's performance, along with the security (i.e., exposure of unique IPs and latent configuration) of our studied allocation policies and adversaries. In so doing, we seek to understand the applicability of EIPSIM towards studying secure IP allocation, as well as whether novel IP allocation policies can strongly mitigate exploitations against IP reuse. Finally, we evaluate our statistical assumptions by performing parallel evaluations on a real-world server allocation dataset, and by examining the behavior of latent configurations from a public cloud Internet telescope.

Note that our main analysis considers a multi-tenant adversary. For completeness, we also include evaluations on single-tenant adversaries (those considered in prior works) in Section 5.4.

5.1. Simulation Parameters and Objectives

Our simulator allows researchers and practitioners to understand the impact of environmental, policy, and adversarial conditions on security properties. As such, it can be tuned with a variety of settings that are useful for analysis. Within this setting, an adversary aims to achieve coverage of the IP pool and associated latent configurations, objectives that we further define here.

IP Count and Utilization. The size of the overall IP pool ($|\mathcal{I}|$), and the number of IPs allocated at any given time $|\mathcal{I}_{A_t}|$) has a substantial impact on allocation performance. If the majority of IP addresses are assigned, for instance, the pool policy has fewer choices when a tenant requests a new IP, and strategies that age, tag, or segment the addresses will therefore be less effective. Here, we can study performance by varying the max pool *allocation ratio* ($AR_{max} = \max_t \frac{|\mathcal{I}_{A_t}|}{|\mathcal{I}|}$) between simulations. Our evaluated simulation scenarios have $\max_t |\mathcal{I}_{A_t}| \approx 680\text{k}$, and compute $|\mathcal{I}|$ using AR_{max} (set in each experiment).

Allocation Duration. Benign and adversarial tenants allocate IP addresses and hold them for some period of time. Study of the duration for which tenants and adversaries allocate IPs can yield insights on countermeasures. Our simulated adversary holds IPs for 10 minutes.

Free Duration. Pools hold free addresses available for allocation, and holding an address for longer decreases the likelihood of associated latent configuration. As such, understanding the distribution of how long pools keep IPs free can suggest measures towards reducing latent configuration.

Latent Configuration Probability. In all simulations, we use a fixed probability of a given tenant leaving latent configuration, $p_c = 0.5$. In separate evaluations, we found that results varied roughly linearly with this parameter, making it less interesting for extensive study. However, future works could use more complex models for latent configuration where this constant plays a greater role.

Adversarial Objectives. Within a given simulation, we seek to understand how effectively an adversary's goal is achieved. Here, an adversary aims to maximize the amount of *latent configuration* that they detect per IP allocated (proportional to total cost). We measure this quantity as *latent configuration yield*, the fraction of IP allocations which yield a (1) unique IP address with (2) some associated latent configuration. While latent configuration yield is the ultimate goal of an adversary, this metric relies on our modeled distribution of latent configuration, and so practitioners may wish to use a metric that does not make assumptions on this model. We therefore also measure *unique IP yield*, which is the fraction of IP allocations which yield a new unique IP address. Cloud providers could use our simulation framework with real-world allocation traces and concrete adversarial behavior, eliminating dependence on our statistical assumptions.

5.2. Performance Evaluation

TABLE 1: Performance scaling of EIPSIM with pool size. Speedup is the amount of simulated time (100 days) divided by time to simulate. EIPSIM scales to model pools with millions of IPs and hundreds of millions of allocations.

# IPs	Runtime	Speedup	Allocations	Allocs/s
100	380 ms	23 M	3 k	8 k
1 k	460 ms	19 M	24 k	51 k
10 k	1.3 s	6.8 M	230 k	180 k
100 k	9.8 s	880 k	2.2 M	230 k
1 M	117 s	74 k	22 M	190 k
10 M	1.7 ks	5 k	220 M	130 k

We briefly analyze the performance of EIPSIM to verify its utility in modeling large public clouds. We simulate non-adversarial scenarios on an AWS `m6a.4xlarge` server with 16 vCPUs and 64GB of RAM, though simulations use only one CPU thread so such analyses could be performed in parallel. In each case, $|\mathcal{I}|/10$ tenants were used with a max concurrent allocation of 10 per tenant. Simulations run for 100 (virtual) days. Results (Table 1) show runtime and allocation rates with respect to pool size, demonstrating that EIPSIM scales with pool size to millions of allocations.

5.3. Non-adversarial Scenario

To understand the aggregate performance of the various IP allocation policies, we first perform a simulation of the pool with no adversary. Here, agents allocate and release IP addresses on behalf of simulated tenants, and we study the effect of these policies on the configurations associated with allocated addresses.

Results are shown in Figure 5. From these simulation results, we can come to several conclusions about the efficacy of our model and simulator, strength of existing and new allocation policies, and insights towards development of new policies.

Tenant Behavior. We first analyze the distribution of tenant allocation durations (Figure 5a). Here, we see that simulated allocations span several orders of magnitude in duration, representing a diverse distribution of behavior. Furthermore, to allocate within the distribution of other tenants an adversary would need to hold IPs and associated servers for an extended period of time, reducing yield for a given cost. This provides hope that adversarial behavior in the pool could be identified and segmented from legitimate users.

Time Between Reuse. Next, we can see differences in how long policies keep IP addresses between reuse (Figure 5c). Results are shown for two allocation ratios ($AR_{max} = 0.8$ and $AR_{max} = 0.97$). These represent low- and high-contention scenarios for the pool, respectively. Beyond $AR_{max} = 0.97$, the policies cannot consistently age IPs for at least 30 minutes before reuse. In both cases, allocation schemes other than LRU perform similarly, reusing IP addresses in as little as 30 minutes, whereas LRU consistently maximizes the minimum time between reuse, by design. While this figure implies that LRU may be superior for preventing latent configuration, other policies that specifically target adversarial allocations may perform better in practice due to other factors.

Pool Behavior Over Time. Looking at prevalence of latent configuration over time in Figure 5b, we initially see lower prevalence as the pool has unused IP addresses to allocate. Beyond that, prevalence for RANDOM and LRU allocation approaches p_c (note that prevalence can exceed p_c as multiple tenants have the opportunity to associate configuration with a given IP address). LRU unsurprisingly outperforms RANDOM slightly, due to the higher time between reuse of IP addresses. While higher time between reuse most clearly reduces aggregate exposure of latent configuration under our posited exponential distribution, cloud providers could also use EIPSIM with other models of latent configuration to validate against their unique scenarios. We expect similar results from any monotonic distribution of d_v.

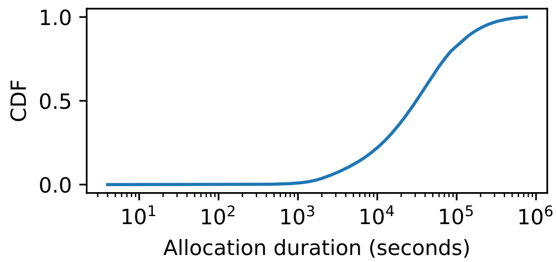
Effect of Pool Utilization. IP addresses are a scarce resource, so cloud providers should aim to achieve the best security against latent configurations while incurring minimal pool size overhead. In Figure 5d, we see that the studied allocation policies have differing behavior as pool size changes. At very high allocation ratios ($AR_{max} > 0.93$), SEGMENTED and TAGGED allocations perform nearly identically and better than RANDOM or LRU strategies. For low allocation ratios, TAGGED eliminates latent configuration under the studied simulation parameters, though this is likely attributable to the short duration of the simulation and corresponding low number of unique tenants. Despite this, our experiments demonstrate that allocation policies can have marked impact on overall latent configuration exposure even for high IP allocation ratios.

Our non-adversarial experiments show that EIPSIM and its associated models are a compelling means by which to study the behavior of IP address pools, spanning a broad range of resulting tenant allocations. Further, the parameters of our initial simulation prove interesting for further study, as the variety of tenant behaviors leads to differentiated performance across allocation policies.

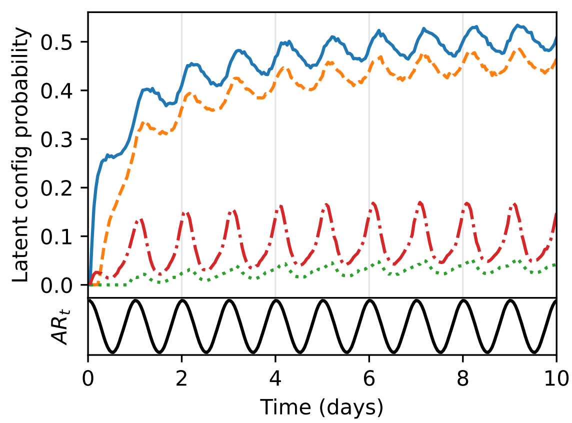
5.4. Single-tenant Adversary

Based on our simulations of the benign pool, we next additionally simulate an adversary that is attempting to explore the IP space and discover latent configurations. To do this, we model each simulation as in the previous section, but then after 10 days (once the pool has stabilized), the adversary is able to begin allocating IP addresses and exploring associated configuration for an additional 10 days. For each simulated adversary, we seek to answer two questions:

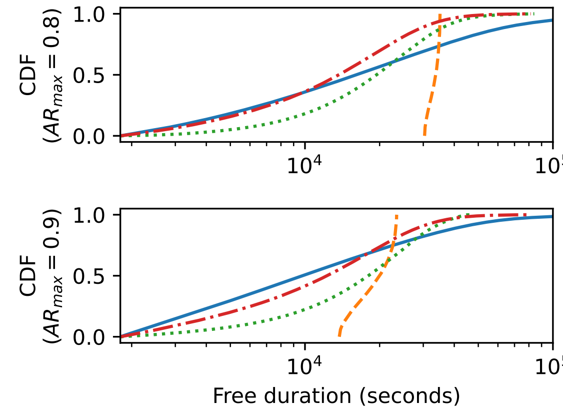
1) How many unique IPs can the adversary discover based on their allocation scheme?



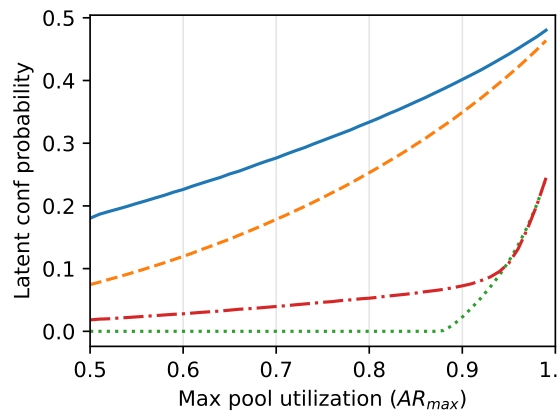
(a) Distribution of tenant allocation durations under the scenario described in Section 5.3. The broad range of allocation durations demonstrates the generality of the simulation parameters for evaluating pool policies.



(b) Latent configuration prevalence over time ($AR_{max} \approx 0.97$). Here, the lower plot shows the instantaneous allocation ratio of the pool over time (AR_t). As the pool reaches max allocation, strategies tend to allocated IPs with more latent configuration as addresses must be reused more quickly.



(c) Distribution of time between reuse across policies for two values of RA_{max}. The LRU pool sees the most impact from having more IPs available, as addresses can be aged for longer.



(d) Overall latent configuration varying max allocation ratio AR_{max}. IP Tagging and Segmentation policies further reduce prevalence even at high allocation ratios.

RANDOM LRU TAGGED SEGMENTED

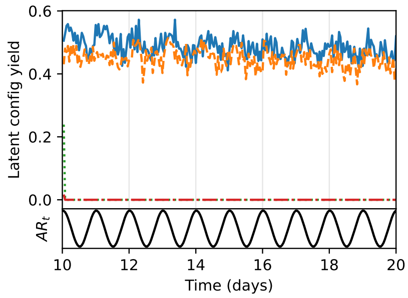
Figure 5: Modeling tenant allocations ($p_c = 0.5$).

2) How many new latent configurations does the adversary discover associated with those IP addresses?

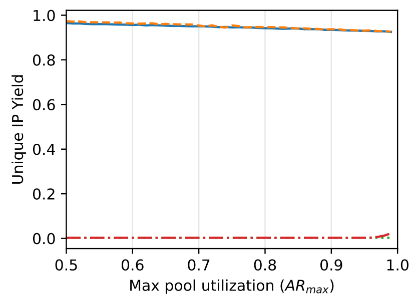
Unique IPs. Figure 6b displays the adversary's ability to discover new IPs across policies and allocation ratio. The RANDOM and LRU policies exhibit roughly identical behavior: IP yield is reduced as the pool gets smaller (AR_{max} gets higher) because the adversary is more likely to receive the same IPs back. Likewise, TAGGED and SEGMENTED both almost completely eliminate the single tenant adversary's ability to discover new IPs. This is unsurprising, as both strategies tag IPs to the most recent tenant and reallocate those IPs back to the tenant. SEGMENTED exhibits a slight increase in adversarial IP yield at very high allocation ratios, as other tenant allocations interfere with the IPs tagged to the adversary–this does not occur in TAGGED because the LRU backup queue prevents the tenant's tagged IPs from being taken.

Latent Configuration. While an adversary might directly seek to observe a high number of IPs, the end goal is to discover IPs that actually have associated configuration. Our results (Figure 6c) demonstrate a marked difference here as well, with both TAGGED and SEGMENTED performing equivalently well against the single-tenant adversary. As seen in the non-adversarial scenario, LRU also slightly outperforms RANDOM as IP addresses are held in the pool longer before reuse, though this effect is diminished as the allocation ratio increases since the policies are best effort and must allocate some available IP to the adversary.

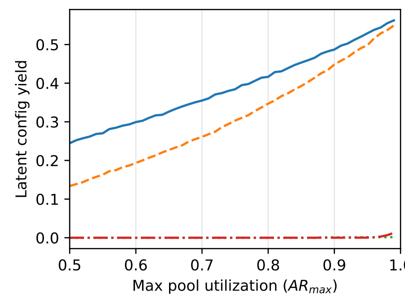
Our tool also allows us to model adversarial objectives over time (Figure 6a). Here, we see that the bulk of latent configuration discovered under TAGGED and SEGMENTED occurs early in the experiment. Beyond this, the pool returns the same IP addresses to the adversary and no latent configurations are discovered.



(a) Yield of new latent configurations over time ($AR_{max}=0.9$). The first 10 simulated days are omitted and identical to Figure 5b.

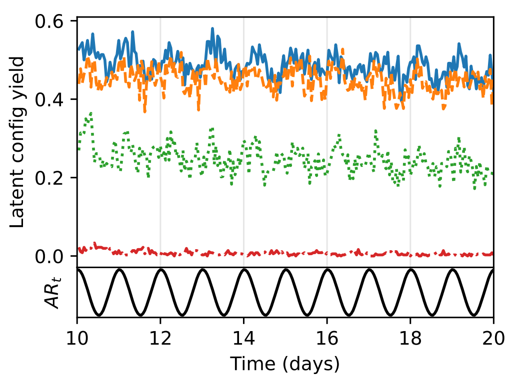


(b) Effect of pool utilization on discovered unique IPs. TAGGED and SEGMENTED strongly protect against the single-tenant adversary up to high pool utilization.

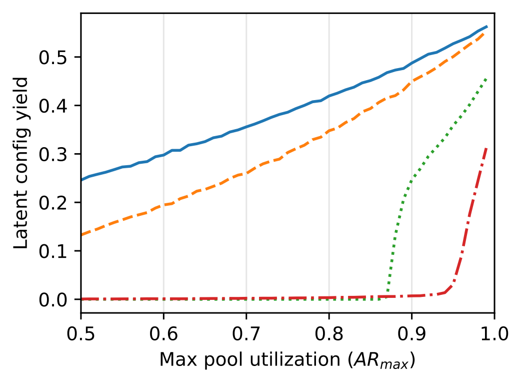


(c) Effect of pool utilization on discovered latent configurations. While LRU provides mild protection vs RANDOM, TAGGED and SEGMENTED have superior performance.

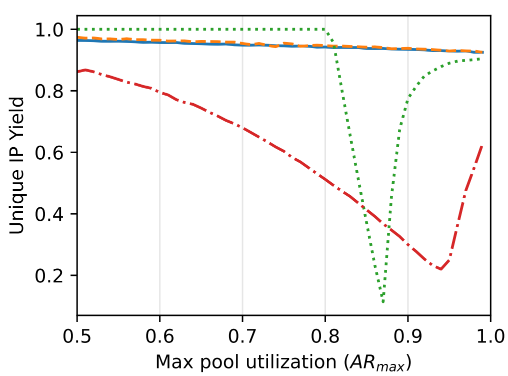
Figure 6: Modeling the single-tenant adversary.



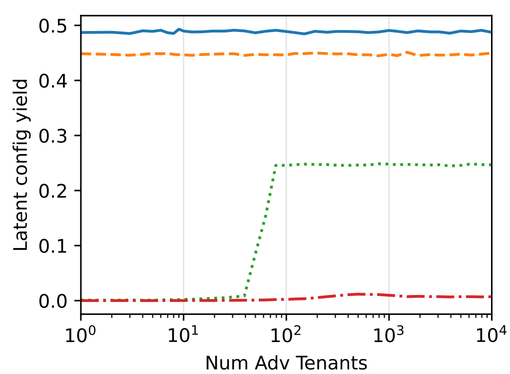
(a) Yield of new latent configurations over time ($AR_{max}=0.9$)



(c) Effect of pool utilization on discovered latent configs (unlimited adversary tenants)



(b) Effect of pool utilization on discovered unique IPs (unlimited adversary tenants)



(d) Effect of total adversary tenants on latent configuration yield ($AR_{max}=0.9$)

Figure 7: Modeling the multi-tenant adversary.

5.5. Multi-tenant Adversary

Next, we evaluate how pool implementations defend against a multi-tenant adversary. Similarly to the single-tenant scenario, we study how an adversary with unlimited tenants can discover new IPs and latent configuration. We also evaluate how an adversary's success varies with the number of tenants they can create.

Unique IPs. Figure 7b shows the number of unique IPs discoverable by an unlimited-tenant adversary as pool utilization varies. While the non-tenant-aware policies RANDOM and LRU show no difference from the single-tenant adversary, tenant-aware policies show surprising results. In both cases, unique IPs reduce as utilization increases to some critical point, then increases again. In each case, while the adversary discovers more IPs at low utilization, these IPs were never associated with another tenant and are therefore not dangerous. Above the critical point, both TAGGED and SEGMENTED must allocate potentially-dangerous IPs to tenants, but SEGMENTED successfully identifies behavior patterns across adversary tenants and reduces the number of unique IPs seen. In this way, SEGMENTED successfully protects a larger portion of the IP space.

Latent Configuration. Figure 7c shows how the multi-tenant adversary's yield of latent configuration varies with allocation ratio. Here, we see the complete effect of tenant-aware allocation policies: below the policy's critical point, allocated IPs have minimal associated latent configuration, so a high unique IP yield does not allow exploitation. Above this, strategies offer only mild protection (i.e., approaching that of non-tenant-aware policies). Most importantly, however, this plot emphasizes the advantages of IP scan segmentation: SEGMENTED reduces latent configuration yield by $500\times$ compared to RANDOM, whereas TAGGED only reduces yield by $14.5\times$. When considering an adversary with the ability to use multiple cloud tenants, TAGGED offers superior protection to prior works and currently-deployed policies.

Looking at a time-series plot of allocations (Figure 7a), we see that TAGGED fails to converge towards protecting the IP pool against exploration for high AR_{max}. However, TAGGED still provides some protection even at these high allocation ratios, likely because it reduces the number of unique IPs with which tenants associate latent configuration. In contrast, SEGMENTED has an initial spike in exposed configurations, but then converges towards a lower yield.

Effect of Tenant Count. A realistic adversary may not have access to create an unlimited number of tenants in the public cloud, due to billing and other compliance measures taken by the provider. As such, it is helpful to understand how adversarial capability scales with number of tenants under various allocation policies. In Figure 7d, we see the marked effect of scaling tenant counts on effectiveness against TAGGED. An adversary begins to increase latent configuration yield above 20 tenants, with peak yields reached at 60 tenants. In contrast, SEGMENTED provides only a slight increase in yields even with no limit on tenants[2].

Our analysis of the multi-tenant adversary demonstrates the limitations of existing allocation policies, as an adversary using many tenants can still discover latent configuration. In contrast, IP scan segmentation's heuristics more effectively segment pool scanning based on the characteristics of allocations, rather than just tenant identifiers, and so are resistant to these attacks. Further, the SEGMENTED pool achieves improved performance even at very high pool contention, approaching the practical limit while maintaining existing minimum reuse durations.

2. A limit of 10^4 in this scenario allows the adversary to never reuse a tenant, so the tenant count is effectively unlimited.

5.6. Tuning Segmentation

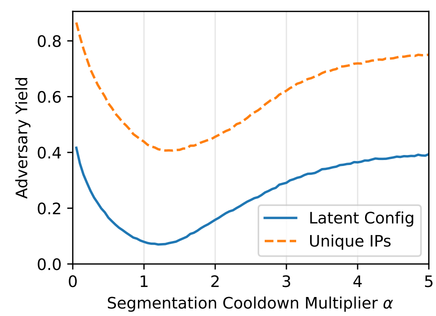


Figure 8: Effect of varying Segmentation parameter α on adversarial yield. ($AR_{max} = 0.9$)

Because the SEGMENTED policy is parameterized by some α, it is important to tune the parameter for optimal performance. Here, we seek to understand how varying α affects adversarial yields under our simulation, and also how cloud providers might model policies on their own traces. To do this, we perform simulations of an unlimited-tenant adversary against a SEGMENTED pool. We vary α and study the yields of unique IPs and latent configuration.

Our results (Figure 8) demonstrate a substantial effect of varying α. Varying α can make up to a $2.1\times$ variation in unique IP yields, and up to a $6.0\times$ variation in latent configuration yield. The relationship between α and adversarial objectives is convex, leading to a clear global optimum for configuration of a deployed system.

In addition to demonstrating an optimal value of α in our simulation setting, our results also suggest that modeling configurations of the SEGMENTED policy could be performed without making as strict of assumptions about latent configuration. Recall that EIPSIM assumes exponentially-distributed latent configuration durations. While a cloud provider could substitute real IP allocation traces, collecting data on concrete configurations is far more difficult. In our results, however, we show that latent configuration and IP yield are highly correlated, so a cloud provider could model IP address yields on concrete data and be confident in applicability to latent configuration yields, as well.

5.7. Validating Latent Configuration

Finally, we evaluate the realism of our model of latent configuration by analyzing the distribution of latent configuration in deployed systems. To do this, we leverage the results of a previous work by Pauley et al. [3]. In this work, IP addresses on a major cloud provider are allocated and released in regular intervals (as in our simulation), and latent configurations are measured based on network traffic. Because many of the IP addresses studied are received many times, prevalence of latent configuration can be analyzed over time. Based on an extended version of this dataset

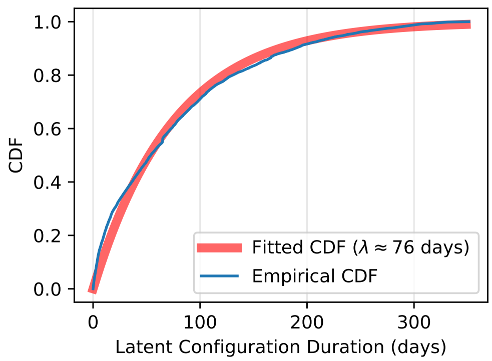


Figure 9: Distributions of latent configuration durations collected on real-world cloud traffic. Latent configuration durations strongly fit to the hypothesized exponential distribution.

(taken over 559 days and covering over 3 million unique IPs), we extract all observed DNS-based latent configurations. For those seen multiple times in the study, we compute the maximum duration each configuration was seen, and use maximum likelihood estimation to fit a corresponding exponential distribution.

The resulting distribution (Figure 9) is strongly consistent with our hypothesized exponential distribution of latent configuration. While characterizing the distribution of latent configuration with respect to the underlying IP address allocation would require data from cloud providers, these empirical results support our statistical models and the effectiveness of our studied policies.

5.8. Evaluating on Real Allocation

We next seek to understand whether our model of IP allocation generalizes to real-world scenarios. To this end, we perform an evaluation of allocation policies against server allocation traces from Google's `clusterdata-2019` dataset[36]. This dataset contains real-world server allocations and usage traces across 31 days in eight independent clusters. While the distinct workloads deployed to these clusters (e.g., many short-lived jobs for MapReduce-type workloads) prevents it from being a perfect analog to public cloud scenarios, it is nonetheless the most comprehensive dataset of service allocations available, and so forms a strong basis for evaluation in the absence of traces from cloud providers.

To extract corresponding IP address allocation traces from allocations in `clusterdata-2019`, we take all Job (groups of processes running as a single collection) allocations across all eight clusters, remove malformed jobs or those running beyond the scope of 31 days, and extract the User of these jobs as a tenant ID. Each Job is assumed to have a public IP address allocated, and latent configuration is modeled over these jobs as previously discussed. The resulting traces contain 24 M allocations across 21 k tenants, with $\max_t |\mathcal{I}_{A_t}| \approx 119\text{k}$.

Results (Figure 10) largely confirm the effectiveness of new IP allocation policies. Here, we see that SEGMENTED prevents discovery of latent configurations by an adversary with unlimited tenants, even at high pool utilization. Notably, `clusterdata-2019`'s composition of short-lived allocations for batch jobs represents a worst-case scenario, with many of these allocations seemingly indistinguishable from those used by an adversary. Yet, the SEGMENTED policy reduces the sharing of long-lived IP allocations with these short-lived tenants, preventing the adversary from discovering IPs with associated latent configuration.

One interesting phenomenon visible on these real-world allocation traces is the non-monotonic effect of tenant count on attack effectiveness. Here, we see that an adversary achieves increasing latent configuration yield with more tenants, then reduced effectiveness once tenants are no longer reused. This is a result of the default reputation of tenants: a new tenant has a d_a/n_a of 0, which is then increased by allocating and releasing IPs. Reusing tenants with this (minimal) increase in reputation affords greater yield, especially when legitimate tenants have similar IP allocation behavior. While this worst-case scenario emphasizes a weakness of the SEGMENTED policy, it is unlikely that similar behavior would be seen in a public cloud, where job-based products such as AWS Lambda and Batch do not assign public IPs to short-lived instances.

6. Discussion

6.1. Simulated vs. Real Tenant Behavior

In this paper, tenant behavior is simulated from a representative distribution as real traces of tenant IP allocation behavior are not available. Our model of tenant allocation behavior takes into account one of the most common instances of tenant allocation workloads, autoscaling infrastructure. To understand this distribution, EIPSIM also allows us to perform parameter-space explorations of simulation, tenant and adversarial parameters.

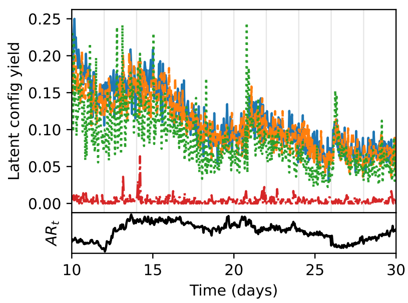
In addtion to our modeled tenant behavior, we also validate EIPSIM on real server allocation traces from `clusterdata-2019`, and EIPSIM can additionally process allocation traces from practitioners in a serialized format. By releasing our tool as free software, we hope that cloud providers will leverage our modeling and framework with real tenant allocation traces [37] to audit/evaluate their policies and develop new mitigations against IP reuse and latent configuration exploitability on their clouds. We also encourage providers to make these more representative traces available to the community in anonymized form to promote further research.

6.2. Implications of d_v

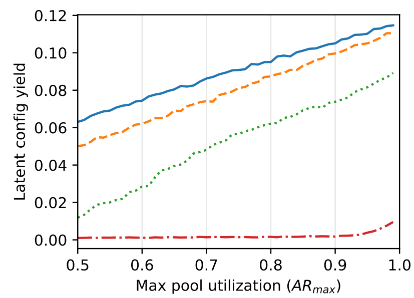
Under our exponential model of vulnerability duration d_v, dissociation is more likely to occur closer to the time of release. Related works in IP assignment duration have used the exponential model to predict the survival of IP addresses [38]. From our model, the rate parameter $\frac{1}{d_a}$ suggests that shorter allocation duration increases the probability of having a longer duration of vulnerability. Further, our analysis of latent configuration from real cloud traces demonstrates the realism of this model.

An intriguing property of the exponential distribution is its *memoryless* nature. This property refers to how the time between events is independent from the elapsed time. In the case of our random variable d_v, this is mathematically defined by

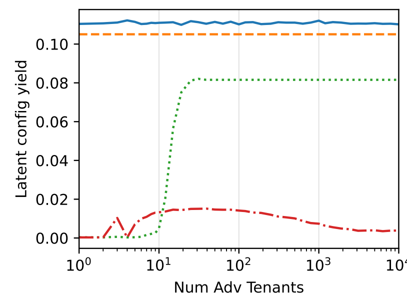
$$\mathbb{P}(d_v > x + s | d_v > x) = \mathbb{P}(d_v > s)$$



(a) Yield of new latent configurations over time (AR_{max} = 0.95).



(b) Effect of pool utilization on latent configurations. The SEGMENTED policy protects real-world deployments even at high pool contention.



(c) Effect of tenant count on latent configurations. Segmented allocation provides substantial protection against a multi-tenant adversary.

Figure 10: Evaluating allocation policies on real-world traces from `clusterdata-2019`.

where x and s are arbitrary times within the domain of the duration of vulnerability d_v. This raises an interesting fact in that even after x amount of time from IP release, the probability distribution for time to dissociation is equivalent to that from the time of release. Further, this implies that at any given time after the IP is released, it cannot be assumed that the probability of time to dissociation will alter. While the exponential distribution's memoryless properties and closed form make it an ideal candidate for our modeling scenario, future work could establish other distributions based on further analysis of tenant deployment scenarios and security practices.

6.3. Allocation Policy Realism

TABLE 2: Largest major cloud compute regions.

Provider	Largest Region	# Zones	# IPs
GCP [39]	`us-central-1`	4	2.8 M
Azure [40]	`eastus`	3	3.3 M
AWS [41]	`us-east-1`	5	16 M

Our proposed allocation policies are designed to provide practical security improvements, and it is therefore important that such policies are realizable. To ensure simulations are deterministic, policies use non-heuristic techniques to select IPs. For instance, the LRU policy maintains a First-In-First-Out queue of IPs. However, such policies can also be implemented heuristically, such as by choosing the LRU IP from a sampled subset of free IPs. All discussed policies have constant size data storage overhead per IP, and policy implementations used for evaluation are as complex as resource-intensive as deployed policies would be. For instance, at the time of writing the largest compute cloud region (See Table 2) is AWS `us-east-1`, with 16 M IPs used for EC2 across 5 availability zones, within the range of our evaluated performance.

We further demonstrate the achievability of new policies by evaluating the real-world behavior of an existing provider and how those map to the information storage requirements of our proposed SEGMENTED policy. In the case of AWS, while allocation is random, AWS also already tags IP addresses with their previous tenant, and allows tenants to reuse released IPs if they have not been allocated to another tenant [42]. This currently-stored data is sufficient to perform the tenant tagging used by SEGMENTED and TAGGED policies. The remainder of the SEGMENTED policy requires associating an additional timestamp with each IP. Candidate IPs are then randomly sampled (as under current policies) and a best-fit IP is selected based on the heuristic. In this way, the SEGMENTED policy can be achieved using the existing data structures implemented by a major provider.

6.4. Allocation Pricing Signals

IP Scan Segmentation aims to increase the cost associated with IP scanning by tracking the amount spent per IP based on allocation time. In real cloud providers, this could motivate further extending the policy by incorporating other pricing signals from the cloud provider. For example, a tenant allocating powerful servers for short periods of batch processing is indistinguishable from scanning using just allocation traces, but the cloud provider could measure the total cost associated with these allocations and distinguish the activity as legitimate. The IP pool is a scarce resource, and so reducing the number of scanner-segmented IPs allocated to these resources will leave more available for scanners, improving policy effectiveness. We anticipate that cloud providers can extend the EIPSIM framework to incorporate these pricing signals and further improve practical security.

7. Conclusion

The way in which cloud IP addresses are allocated has a substantial impact on the security of hosted applications. Our work proposes new models for cloud IP allocation, and in so doing demonstrates new threat models and resulting defenses to secure cloud infrastructure. Our tool, EIPSIM, implements our proposed models towards developing and evaluating new IP allocation policies. Further, our proposed new policy, IP scan segmentation, successfully reduces an adversary's ability to scan the IP pool even if they can create new cloud tenants without limit. We anticipate that EIPSIM will prove useful to cloud providers to evaluate their IP allocation policies and develop new strategies to protect their customers.

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Appendix

Symbol	*Meaning*
a_i	Fourier amplitude
AR_{max}	maximum pool allocation ratio
AR_t	pool allocation ratio
$\mathcal{B}$	distribution of tenant behaviors
B_i	behavior of tenant i
d	duration
d_a	duration of allocation
d_{reuse}	minimum time duration before an IP can be reused
d_v	duration of vulnerability
$\mathcal{I}$	set of all IP addresses
$\mathcal{I}_{A_t}$	set of IP addresses currently allocated
p	probability
p_c	probability of latent configuration
S_{max}	maximum number of servers
S_{min}	minimum number of servers
t	time
t_a	allocation time
t_c	time of configuration dissociation
t_{cd}	cooldown time
t_r	release time
T	tenant ID
α	segmentation cooldown multiplier
ϕ_i	Fourier phase
θ	opaque state

Additional Implementation Details

To empirically study the interaction of IP allocation behaviors, adversarial techniques, and deployable defenses, we develop the Elastic IP Simulator (EIPSIM). While the the scale of cloud computing as astronomical, the allocation of IP addresses occurs and can be simulated independently. While the space of these addresses is still quite large ($\approx$16M) for the largest AWS cloud region, this is still within the realm of exact simulation. To this end, EIPSIM simulates concrete tenant and cloud provider behavior at IP- and second-level granularity.

Within this architecture, *agents* perform the behavior of tenants, either by simulating tenant behavior or by replaying allocation traces from a previous run of the simulator or from actual tenants. The simulator fulfills IP allocation requests from these agents by referring to implementations of an *IP pool policy*. Each agent has the ability to allocate IPs under multiple tenant IDs, and the simulator treats these allocations as though they come from different tenants. While processing allocations, the simulator records statistics on the lifecycle of addresses, associated latent configuration, and adversarial objectives. Importantly, while these results are aggregated across addresses and tenants, they are a product of granular simulation of each tenant IP allocation.

1. Tenant Agents

EIPSIM relies on tenant agents to perform the allocations of tenants. At each time-step (1 s) the simulator allows each agent to perform actions. Benign behaviors can be simulated by one of two agents:

- The *benign tenant agent* simulates the allocation behavior of tenants scaling cloud resources (Section 3.1. For each tenant managed by the agent, and at each time-step, the agent checks if the tenant should allocate or release IP addresses, and passes these actions back to the simulator.
- The *file agent* allows loading of tenant behaviors from a time-series file. This file contains the timestamps and tenant IDs of each IP allocation and release from either a previous run of EIPSIM or recorded from a live cloud environment (such as Google's clusters in Section 5.8).

The *adversarial agent* is a specialized agent designed to simulate and analyze the behavior of a single- or multi-tenant adversary. The adversarial agent performs allocations exactly as it would on a real system (except that allocation requests are passed to the simulator instead of a cloud provider), and proceeds in several steps:

1) The agent requests IP addresses from the provider up to some quota (the maximum number of IPs it will hold at once). It records previous tenants and latent configuration associated with these for analysis (in reality an adversary would listen for network traffic or search DNS databases to identify these [3], [1], [2]).
2) The agent holds these IPs for a fixed duration. In EIPSIM, this is accomplished by performing no action when called by the simulator during this time.
3) The agent releases IPs that have been held for the specified duration back to the pool.
4) In the case of a multi-tenant adversary, new IPs are allocated under new tenant IDs. After a maximum tenant ID is reached, the adversary loops back to the initial tenant, simulating an adversary with access to only a fixed number of tenants.

While the techniques employed by the adversary could be performed by any cloud customer, the adversarial agent has access to the internal data structures of the simulator to be able to record time-series data on the functioning of the pool. For instance, when the agent allocates IP addresses it can access the list of previous tenants associated with that address (as this is used by our analysis).

2. Allocation Policies

When the simulator receives a request for an IP address from a tenant, it forwards it to an allocation policy for servicing. While the simulator tracks what IP addresses are in use at any time, it is ultimate up to the policy to determine which free IP address is allocated to a given tenant. The policy receives the tenant ID associated with each allocation, but is not told the agent performing the request, or if the tenant is adversarial. The policy must also service all requests, though it may return any free IP for a given request.

The policy contains data structures that can track the history of a given IP address. For instance, the SEGMENTED policy tracks the most recent tenant ID for each IP, the cooldown time, and the average allocation durations of tenants. When a tenant requests an IP address, it heuristically samples available IPs that best conform to the policy based on this data. Considerations for deploying policies in practice are discussed in Section 6.3.

3. Extending the EIPSIM Framework

EIPSIM supports expansion to new policies, behaviors, and adversaries as academics and practitioners continue to study cloud IP allocation. EIPSIM defines `interfaces` between components, and new components can be added either as part of the EIPSIM package, or within a separate program that uses EIPSIM as a library. EIPSIM provides convenience functions to ease in the development of new components: for example, our studied allocation policies were implemented in an average of 71 lines of code, and new parameter sweep tests can be built on top of EIPSIM in around 70 lines of code. We expect that, by encouraging the development of new components on top of our framework, the community can reach a unified means to compare threat models and defenses. EIPSIM also supports allocation traces collected by cloud providers through custom agents. Practitioners can directly read allocations as tuples of (T, t_a, t_r) and use EIPSIM to simulate adversarial and pool behavior.

Data Availability

EIPSIM is proposed as a theoretical and applied framework for studying the security of IP address allocation. As such, code and evaluation artifacts will be made available to reproduce results and support further study by practitioners. Code for EIPSIM, the evaluation, and figures will be released under a permissive open source license. The `clusterdata-2019` dataset (used in Section 5.8) is freely available, and data preparation code will be provided. Data used in Section 5.7 is provided by the authors of the referenced prior work, and cannot be openly shared for privacy reasons (as the underlying data refers to concrete instances of vulnerable configurations).