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Author(s): Guanhua Yan, Z# 208461, CCS-3
Stephan Eidenbenz, Z# 173410, CCS-3
Songqing Chen, George Mason University

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RatBot: Anti-Enumeration Peer-to-Peer Botnets

Guanhua Yan[†] Songqing Chen[‡] Stephan Eidenbenz[†]

[†] Information Sciences (CCS-3)
Los Alamos National Laboratory

[‡] Department of Computer Science
George Mason University

Abstract

Botnets have emerged as one of the most severe cyber threats in recent years. To obtain high resilience against a single point of failure, the new generation of botnets have adopted the peer-to-peer (P2P) structure. One critical question regarding these P2P botnets is: how big are they indeed? To address this question, researchers have proposed both actively crawling and passively monitoring methods [15, 14, 13] to enumerate existing P2P botnets. In this work, we go further to explore the potential strategies that botnets may have to obfuscate their true sizes. Towards this end, this paper introduces RatBot, a P2P botnet that applies some statistical techniques to defeat existing P2P botnet enumeration methods. The key ideas of RatBot are two-fold: (1) there exist a fraction of bots that are indistinguishable from their fake identities, which are spoofing IP addresses they use to hide themselves; (2) we use a heavy-tailed distribution to generate the number of fake identities for each of these bots so that the sum of observed fake identities converges only slowly and thus has high variation. We use large-scale high-fidelity simulation to quantify the estimation errors under diverse settings, and the results show that a naive enumeration technique can overestimate the sizes of P2P botnets by one order of magnitude. We believe that our work reveals new challenges of accurately estimating the sizes of P2P botnets, and hope that it will raise the awareness of security practitioners with these challenges. We further suggest a few countermeasures that can potentially defeat RatBot's anti-enumeration scheme.

1 Introduction

Peer-to-peer botnets have gained a lot of attention in the research community due to the exposure of the Storm botnet, which was first spotted in 2007. Compared with the first generation of botnets that commonly relied on IRC channels for C&C (Command and Control) delivery, peer-to-peer botnets do not suffer a single point of failure and are thus difficult to disrupt. Due to the lack of a central controller, a challenging yet intriguing question regarding peer-to-peer botnets is: *how big are they indeed?* The effort of seeking the answer to this question is not only driven by our curiosity but also justified by the fact that knowing the size of a botnet sheds light on its attack capacity, that is, how many zombie machines the botmaster can control at his will.

Since the inception of the Storm botnet, there have been a few endeavors to estimate its exact size, which sometimes led to inconsistent results. Some researchers estimated that the original Storm botnet possessed as many as 50 million zombie machines [27]. Kanich et al. developed a crawler called Stormdrain, which identified Storm bots by looking for nodes that searched hashes specific to the Storm botnet, and concluded that the actual size of the Storm botnet was likely smaller than 40,000 [15]. Recently, Kang et al. made another attempt to estimate the size of the Storm botnet. They adopted a

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passive monitoring approach and found more than 500,000 unique IP addresses in the Storm botnet [14]. Albeit it is true that the Storm botnet has been evolving since its debut, thus leading to different results if measured at different times, it is difficult to quantify the errors of these estimates due to the lack of ground truth regarding its real size.

What makes the situation worse is that peer-to-peer botnets may use obfuscation techniques to foil attempts to estimate their actual sizes. In this work, through the demonstration of a hypothetical peer-to-peer botnet called RatBot, we shall show that such techniques do exist and can actually lead to highly variable estimates on botnet sizes. The key ideas of RatBot are two-fold: (1) there exist a fraction of bots that are indistinguishable from their fake identities, which are spoofing IP addresses they use to hide themselves; (2) we use a heavy-tailed distribution to generate the numebr of fake identities for each of these bots so that the sum of observed fake identities converges only slowly and thus has high variation. These two techniques render it difficult to infer the exact sizes of this type of P2P botnets by enumerating participating bots.

To demonstrate the practical feasibility of RatBot, we implement it based on KAD, a popular P2P protocol. We use the actual development code of aMule, a P2P client software that uses KAD for its P2P communications [2]. We further develop a distributed simulation testbed to evaluate the effectiveness of RatBot in misleading the estimation on the botnet sizes. We perform a variety of tests with different settings and the results show that a naive botnet enumeration approach by counting the IP addresses observed from the P2P botnets could overestimate their sizes by one order of magnitude.

The goal of our work is to raise the awareness of white-hat cyber-security practitioners on the challenges of inferring botnet sizes. Measurement works on existing P2P botnets have highlighted some difficulties on estimating their sizes accurately, such as DHCP and NAT effects [14, 30], but our work shows that even if we deploy advanced techniques to sift out these factors, the botnets themshelves can still apply obfuscation techniques to make it a difficult task to estimate their sizes accurately. Moreover, although there have been previous efforts on exploring hypothetical P2P-based botnets with high resilience [29], delay tolerance [7], and membership hiding using sophisticated encryption [23], this work fills the gap of understanding potential strategies that attackers may have on obfuscating the sizes of P2P-based botnets. In our work, we use large-scale high-fidelity botnet simulation to quantify the errors of botnet size estimation, which has not been pursued before.

The remainder of this paper is organized as follows. Section 2 presents related work and Section 3 gives the the threat model considered by this work. In Section 4, we discuss the design of RatBot, which is aimed at obfuscating the estimation of botnet sizes, and provide the rationale of such design in Section 5. We introduce the implementation of RatBot based on KAD in Section 6 and use large-scale simulation to evaluate the performance of RatBot in Section 7. In Section 8, we further discuss potential countermeasures against RatBot and draw concluding remarks in Section 9.

2 Related Work

Behaviors of real-world botnets have been analyzed and this line of work has provided tremendous insights into how botnets operate in reality [3, 20, 13, 15, 14]. Our work on studying enumeration of P2P botnets was particularly motivated by the measurement work done by Holz et al. [13] and Kang et al. [14]. Complementary to their efforts, our work sheds light on the potential challenges regarding enumerating zombie machines in P2P botnets accurately. In spirit, our work is similar to that of Rajab et al. [21] as both explore the challenges of estimating botnet sizes. Our work, however, focuses on P2P botnets while theirs is primarily concerned with IRC botnets. Although like RatBot, the cloning technique mentioned in their work also leads to overestimated botnet sizes, the implementations differ drastically due to different botnet structures. Some previous work has shown that multiple factors contribute to inaccurate botnet size estimation, including DHCP and NAT effects [26]. Our results show that even if advanced techniques are deployed to sift out these effects [14, 30], the botnet can still adopt sophisticated obfuscation techniques to make it a difficult task to estimate its size accurately.

To counter the severe cyber threats posed by botnets, a plethora of detection techniques have been developed recently. Gu et al. have proposed a series of bot detection methods exploiting spatial-temporal correlation inherent in bot activities [11, 10, 12]. A technique using virtual machines to detect bot-like activities on individual hosts have also been developed [17]. Other botnet detection techniques include DNS-based methods [22], ISP-level analysis [16], signature-based approaches [9, 31], and flow-level aggregation and mining [32]. Our work is orthogonal to these efforts and focuses on the challenges of estimating botnet sizes.

A number of efforts have been dedicated to understanding potential threats by hypothetic botnets, such as Super-Botnet [28], Overbot [23], delay-tolerant botnets [7], and hybrid P2P botnets [29]. Our work differs significantly from this line of work on two aspects. First, our work focuses specifically on hypothetic P2P botnets that use obfuscation techniques to render it difficult to estimate their true sizes. Second, we have used large-scale high-fidelity simulation to quantify the estimation errors under diverse settings rather than present the design from a conceptual level.

3 Threat Model

In this work, we consider two families of P2P botnets: *immersive P2P botnets* and *exclusive P2P botnets*. For an immersive P2P botnet, the botmaster delivers C&C information through a P2P network that has normal P2P users besides bots. The original Storm botnet, for instance, was an immersive P2P botnet because the C&C information was delivered to the Storm bots through the Overnet network. An exclusive P2P botnet, by contrast, has bots exclusively as its peers and thus does not have any normal P2P user traffic in it. Since the Overnet network was shut down, the Storm botnet became an exclusive P2P botnet dubbed Stormnet because only bots can participate in the botnet after some authentication.

The two primitive operations in a P2P network are *publish* and *search*. The *publish* primitive is used to publish a data item either on the machine used by the caller itself (e.g., in an unstructured P2P network like Gnutella) or on a machine with an identifier that is close to that of the data object (e.g., in a structured P2P network like Kademlia). The *search* primitive is used by a peer node to search for data items that satisfy some specific conditions, such as containing certain keywords or producing a certain hash digest. In this work, we assume that in the P2P network *search* operations are *spoofable*, that is to say, a peer node can request a peer to find a data item using a spoofed source IP address. This holds for many P2P networks, which use UDP to implement the request/response mechanism in a search operation. For instance, the widely deployed KAD protocol uses UDP for signaling and TCP for data transfers [19]; hence, the search operation in KAD is spoofable.

It will be seen later that spoofable search operations play a key role in the design of RatBot for hiding authentic search operations. It is, however, noted that these constraints limit the design of RatBot only if it is implemented as an immersive P2P botnet. For an exclusive P2P botnet, as bots do not require an existing P2P network for their C&C communications, the botmaster has more freedom on the implementation of spoofable search operations.

In this work, we assume a strong adversarial model from the attacker's standpoint. First, we do not assume that the P2P botnet deploys a strong authentication scheme. The recent efforts of successfully reverse-engineering the Storm bot executable have suggested that it is possible to reveal secret keys used for bot communications through static or dynamic malware analysis [13, 14]. A white-hat security analyst can thus create fake bots to infiltrate into the P2P botnet, as demonstrated in some previous work [13, 14]. Second, we also assume that the white-hat security analyst, through thorough static code analysis, possesses full knowledge on the functionalities of an authentic bot, including its communication protocol and anti-enumeration techniques. Third, we assume that the behaviors of a fake bot and an

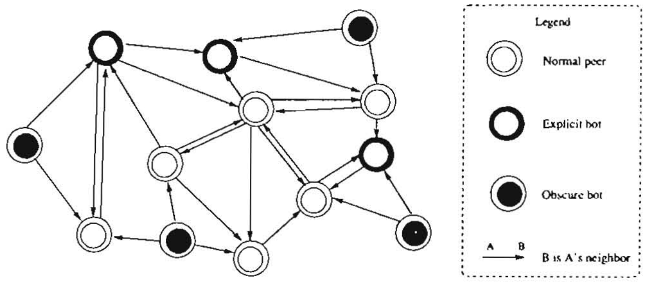


Figure 1. RatBot Architecture

authentic bot are indistinguishable to the bots. A fake bot can intercept any message that passes through it, thus obtaining the source IP address it has used. Fourth, a fake bot may also stay in the P2P botnet for a long time so that for some P2P protocols (e.g., KAD) a large number of peer nodes would add it to their contact lists, or actively crawl the P2P network to obtain a list of observed P2P nodes.

In the remain~~ing~~der of this paper, we will use the *adversary* and the *white-hat security analyst* interchangeably. Even with a strong adversarial model, we, through the demonstration of RatBot, shall show that an anti-enumeration P2P botnet can be designed in such a way that it is difficult for the adversary to estimate the exact number of authentic bots in it.

4 RatBot Design

The key idea of RatBot is the existence of an army of *obscure bots*, each of which creates a list of fake identities to hide itself. In this work, we assume that the identity of a bot is manifested as the IP address that it uses to communicate with other peers in the network. Although the P2P identifier (e.g., KAD ID) of a bot can also be used for enumeration purpose, these identifiers sometimes can be changed by bots, thus leading to inaccurate estimate of the botnet size. Moreover, a compromised machine can run multiple instances of bot executable and counting each instance as a bot overestimates the size of a botnet and thus its attack capacity.

As opposed to obscure bots, we say the remaining bots are *explicit bots*. In the following discussion, we assume a strong adversarial model in which all explicit bots can be enumerated. In Figure 1, we present the architecture of RatBot in the form of an immersive P2P botnet. If RatBot is an exclusive P2P botnet, no normal peers would exist in the figure.

4.1 Obscure Bot Selection

When a machine is infected and becomes a bot, it decides whether it should be an obscure bot. An obscure bot uses spoofed IP packets to hide its true identity. It is therefore crucial that an obscure bot must be able to spoof IP packets. Not every end host in the Internet, however, possesses such a capability for a few reasons [4]. A packet spoofed by a machine behind NAT (Network Address Translation) may not reach the destination because its packet header is rewritten or even dropped by the NAT device because it violates the binding of link-layer and IP addresses. Some networks may block outbound packets with spoofed IP addresses at their firewalls. Also, it is possible that the operating system does not allow ~~to send~~ spoofed packets. Due to these reasons, Beverly et al. found that among 12,000 client machines volunteered by Internet users, only 31% of them are able to spoof an arbitrary, routable source address [4].

As a bot may not be able to decide whether it can spoof IP packets by itself, we let each bot contact a dedicated server during its bootstrapping phase. The server is hardcoded in the bot executable code[1].

[1]In order to improve the resilience of the botnet, multiple servers can be specified in the executable code. Also, fast flux

When a bot contacts a server, it generates a UDP *query* packet with an arbitrary spoofed source; the payload of the packet carries the authentic IP address of the bot. If the packet arrives at the server, it means that the bot is capable of spoofing. The server decides whether the bot should become an obscure bot and if so, sends back a *response* packet to the bot using its authentic IP address carried in the query packet. If the bot receives the response packet within a certain period of time, it becomes an obscure bot; otherwise, it is an explicit bot.

How does the server decide whether a bot should be an obscure bot? Suppose that it knows the size of the current botnet; this can be done by simply letting each newly infected bot report to it using their authentic IP addresses. The server then makes its decision by aiming to have a fraction ξ of the entire botnet as obscure bots. ξ is *not* hardcoded in the bot executable and it is thus not known to the adversary. Hence, the adversary cannot estimate the botnet size as $m/(1-\xi)$, where m is the number of explicit bots that he has observed.

4.2 Identity Obfuscation

Once a bot decides that it is an obscure bot, it randomly generates a list of spoofing IP addresses that it will use to obfuscate its own IP address later in P2P communications. For a given obsecure bot, how many spoofing IP addresses does it create? The answer provides a key role in the level of difficulty for the adversary to infer the correct size of the botnet. Consider a simple scheme in which each obscure bot generates a constant number k of spoofing IP addresses. Suppose that the adversary can obtain a set of IP addresses S that do not respond to normal P2P requests as completely as possible. Then, the number of obscure bots can be estimated at $|S|/(k+1)$ if it is assumed that spoofing IP addresses do not overlap. It is noted that as obscure bots generate spoofing IP addresses independently, these spoofing IP addresses may overlap in practice. Given that the large IP address space to spoof, such overlapping likelihood should be low. The existence of overlapping spoofing IP addresses leads to a smaller number of IP addresses observed by the adversary.

Consider a botnet with n obscure bots. Let X_i denote the number of spoofing IP addresses each obscure bot i generates. RatBot uses two levels of obfuscation for X_i. For the first level (**distribution-level obfuscation**), RatBot uses a distribution with high variation to generate X_i. We consider the Pareto distribution, whose density function is given by:

$$f(x) = \begin{cases} \frac{\alpha x_m^\alpha}{x^{\alpha+1}} & \text{for } x \geq x_m, \\ 0 & \text{for } x < x_m, \end{cases}$$

where x_m and α are the *cutoff* and *scale* parameters, respectively. The mean of the Pareto distribution is $\alpha x_m/(\alpha-1)$ and its variance is $(x_m/(\alpha-1))^2 \cdot \alpha/(\alpha-2)$. It is noted that when $\alpha \leq 2$, the variance becomes infinite. If we set $\alpha \leq 2$, then we cannot apply the central limit theorem on $\sum_{i=1}^{n} X_i$ due to the infinite variance. It is noted that X_i drawn from the Pareto distribution is a float number. In practice, we generate $\lfloor X_i \rfloor$ spoofing IP addresses for sure, where $\lfloor x \rfloor$ denotes the largest integer no greater than x, and an extra one with probability $X_i - \lfloor X_i \rfloor$.

In Section 5, we shall present the rationale behind using the Pareto distribution for generating X_i and also its limitation. To make size estimation even more difficult, RatBot employs another level of obfuscation in generating X_i (**parameter-level obfuscation**). Instead of using a fixed mean for X_i, the mean of X_i on the i-th obscure actually depends on certain attributes of the bot itself. Measurements from the Storm botnet suggest that bot infection is not uniformly distributed either over different ASes or geographically [5]. Provided this observation, we let the mean number of spoofing IP addresses generated by an obscure bot be a function of the time zone where the bot is located. In previous works, security

techniques can be used to prevent easy disruption by the adversary.

analysts use the observed IP addresses to derive that their geographic locations using IP geolocation tools [1] and thus their corresponding time zones. ~~As~~ now spoofed IP addresses are used, it is difficult to accurately infer the time zone of each bot, which renders it hard to estimate the mean of each X_i.

An obscure bot may use a dynamic IP address to communicate with other peers. Whenever the obscure bot observes that the IP address of the hosting machine has changed, it uses the above method to regenerate its spoofing IP addresses.

4.3 Bot Behavior Description

In a typical P2P protocol, a packet between two peers can be classified into three categories: request, response, and data transfer. It is noted that TCP makes spoofing difficult because it requires handshaking between peers. In many normal P2P networks, request and response signaling packets are delivered through UDP and data transfer uses TCP. We consider the two cases in the following. (1) If the P2P botnet is an exclusive P2P botnet, UDP can be chosen by design for delivering all request, response and data transfer packets. (2) If the P2P botnet is an immersive ~~P2P botnet~~, the botmaster does not have the freedom to choose the transport layer protocol. In this study, we assume that request and response signaling packets use UDP. If bot communications do not involve any data transfer packets, spoofing becomes much easier; however, if the P2P protocol uses TCP for data transfer *and* bots need data transfer for command & control, it leaves a door for more accurate bot size estimation by the adversary, as will be explained in Section 8.

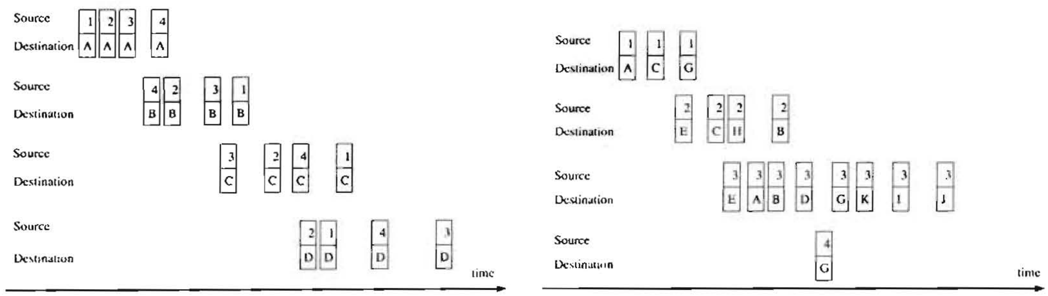
For an explicit bot, its behavior conforms to the standard P2P protocol. For an obscure bot b, let $\mathcal{I}(b)$ denote the set of spoofing IP addresses associated with it. The behaviors of an obscure bot are given as follows.

Response packets. An obscure bot does not respond to any request by another peer. On the arrival of a request packet, it silently drops the packet. As the packet is delivered through UDP, which is connectionless, the origin of the request packet does not know whether the recipient receives the packet or not.

Request packets. We first consider a naive *packet-level* obfuscation scheme for request packets and then present its weakness. When an obscure bot b needs to send out a request packet to peer A at time t, it replicates the packet for $|\mathcal{I}(b)|$ times and each of these packets uses a distinct source IP address from set $\mathcal{I}(b)$. Including the original request packet, there are in total $|\mathcal{I}(b)| + 1$ packets to be sent to peer A. For each obscure bot, we define its obfuscation window as w time units. We *randomly* reorder the $|\mathcal{I}(b)| + 1$ packets as p_0, p_1, ..., and $p_{|\mathcal{I}(b)|}$. Packet p_0 is sent out at time t. The interval between the sending times of packet p_i and p_{i+1} where $i = 0, 1, ..., |\mathcal{I}(b)|$ is drawn from an exponential distribution with mean $w/|\mathcal{I}(b)|$.

As the order of the packets is random, the recipient peer, if it is a monitoring node by the adversary, cannot determine which packet carries the authentic source IP address. The problem with this scheme is that every time a request packet with an authentic source IP is sent, packets with all associated spoofing IP addresses are also sent to the recipient. Hence, if the recipient is a monitoring node deployed by the adversary, she can cluster IP addresses with the same (or approximately the same) number of appearances within w time units. It is highly unlikely that source IP addresses in normal requests packet would show such strong correlation as in the naive obfuscation scheme. As such, even though the adversary does not know exactly which source IP address is authentic, he can still infer the actual size of the botnet by assuming that IP addresses frequently appearing in the same interval of w time units would come from the same obscure bot.

It is noted that request packets are usually used by a bot to search for C&C messages from the botmaster. Hence, to prevent correlation-based analysis, RatBot uses a *session-level* obfuscation scheme for each search operation. Figure 2 illustrates the difference between packet-level and session-level obfusca-



(1) Packet-level obfuscation (2) Session-level obfuscation

Figure 2. Obfuscation comparison

tion. Suppose that an obscure bot needs to find a data item with key $\mathcal{K}$. We call it an *authentic session*, which contains the whole sequence of the peer nodes this bot has contacted in order to accomplish this search operation.

For each of its spoofing IP addresses, the obscure bot will create a *spoofing session*, which contains a sequence of peer nodes that are randomly drawn from a local peer node repository. This repository, denoted $\mathcal{R}$, contains peers that were observed in the past authentic sessions and also the current neighbors that the obscure bot knows. It is noted that peers in an authentic session may appear with a certain order. For instance, when a bot searches a data item with key $\mathcal{K}$ in a DHT P2P network, peers in the authentic session are ordered (or partially ordered) in their distances from key ID $\mathcal{K}$. Hence, when constructing the sequence of peers in a spoofing session, such orders are also mimicked.

The intervals between the starting times of sessions, including both authentic and spoofing ones, are randomly drawn from an exponential distribution with mean γ time units. The order of the starting times of spoofing sessions is randomized. The authentic session is inserted among the top ϕ spoofing sessions, if there are so many, and its place is also randomly chosen. The decision on ϕ should make it difficult to tell which session is authentic but meanwhile ensure that the start of the authentic session would not be postponed significantly due to obfuscation. In our implementation, we let ϕ be 5.

Let Ψ denote the empirical distribution of the number of request packets sent in an authentic session. For each spoofing session, we use Ψ to generate the number of request packets. Each of these request packet carries the spoofing IP address as its source IP and search key $\mathcal{K}$, and is sent to every peer node in the corresponding spoofing session. The interval between two request packets is randomly drawn from the empirical distribution of the intervals between request packets in the past authentic sessions. We use Γ to denote this distribution. To obtain Ψ and Γ quickly, the obscure bot can search data objects with keys that are randomly generated.

When the host machine of the obscure bot powers off, the bot automatically becomes offline and all the packets scheduled to be transmitted before that are lost and thus not carried over to the next time when the machine becomes online again. Hence, the bot does not need to keep states on a permanent storage.

Data transfer packets. If botnet C&C information is stored as a file in a P2P network, each bot needs to fetch the file from the host machine. If RatBot is designed to be an exclusive P2P botnet, UDP can be chosen for data transfer. Otherwise, if it is an immersive P2P botnet, RatBot makes its decisions in the following order: (1) If the C&C information can be spread without involving data transfer, RatBot will not use data transfer. For instance, C&C information can be stored as metadata tags in a KAD-based P2P network. (2) If the P2P network allows UDP for data transfer, RatBot will use UDP instead of TCP for data transfer. (3) Only if the P2P network uses only TCP for data transfer, RatBot would use TCP. It is noted that the third option exposes the identity of obscure bots if the peer hosting the

C&C information is actually a monitoring node deployed the adversary. This is because TCP requires a three-way handshake between the obscure bot and thus the host machine and the connection cannot be spoofed.

5 Rationale and Analysis

In this section, we explain why a high variance distribution such as the Pareto distribution is used to generate X_i in Section 4.2. As we assume a strong adversarial model in which the adversary knows the distribution used to generated X_i, we must ensure that the adversary's knowledge does not lead to a good estimation of the botnet size. The adversary also knows that that an observed IP address cannot be from an explicit bot if it is used in response packets. Let M be the number of IP addresses observed by the adversary that never respond to any requests. The challenge is: can the adversary infer the number of obscure bots provided that he knows the distribution used to generate X_i?

If only the distribution-level obfuscation is used, all X_i are independent and identically-distributed random variables. According to the *law of large numbers*, $\sum_{i=1}^{n} X_i$ always approaches $n\mu$, where μ is the mean of X_i, **when n is large**. As the adversary knows the distribution and thus μ, he can estimate the botnet size as $M/(\mu+1)$. To defeat this type of inference, it is necessary to use a distribution that converges so slowly that $\sum_{i=1}^{n} X_i$ can still be far away from $n\mu$ at reasonable scales of botnet sizes.

The *Chebyshev's inequality* tells us that $\mathbb{P}\{|Y - \bar{Y}| \geq t\} \leq t^{-2}Var(Y)$, where $\bar{Y}$ and $Var(Y)$ are the mean and variance of random variable Y, respectively. Hence, the convergence speed of $\sum_{i=1}^{n} X_i$ is affected by the variation of X_i. That explains our choice of the Pareto distribution: for $\alpha < 2$, its variation is infinite and thus slows down the convergence of $\sum_{i=1}^{n} X_i$. This is further illustrated by the following empirical example.

Suppose that there are 10,000 obscure bots and the average number of spoofing IP addresses an obscure bot generates is 20. We consider four different settings for the scale parameter: $\alpha = 1.01$, 1.1, 1.5, and 1.8. We set the cutoff parameter accordingly to obtain the same mean for X_i. We simulate 1000 cases with different random number generation seeds. In each case, we assume that the adversary sees all the obscure and spoofed IP addresses. Let the observed total number be M. The adversary estimates the number of actual obscure IP addresses as $M/21$ as each obscure IP address has 20 spoofed ones. The following table shows the mean and the standard deviation of the adversary's estimation:

α	1.01	1.1	1.5	1.8
mean	23596.80	81758.83	99854.08	99962.19
std	83014.82	91258.15	4553.54	1262.98

From the table, it is clear that when α is close to 1, the variability of the estimated bot size becomes more significant. For instance, when $\alpha = 1.01$, even after 1000 sample runs, the derived mean is still far away from the actual one, which is 100000. In reality, the adversary witnesses the result of only one sample; hence, if α is small and thus the variability is very high, the adversary will get an estimate on the botnet size with high variation.

It is however important to understand the limitation of using heavy tailed distributions such as the Pareto distribution in generating X_i, even though they can produce highly variable results. The high variation of these distributions actually results from their high skewness in their probability density functions. Figure 3 depicts the probability density function of the Pareto distribution when $\alpha = 1.01$ and the mean is 20. Clearly, it is highly skewed as $\mathbb{P}(X_i \leq 1) = 0.805$, which means that around 80% of the data points, if drawn from this distribution, would stay below 1.

To see how this would help the adversary estimate the actual size of the botnet, we simulate the observed number of spoofing IPs when there are 1000, 10000, 100000, and 1000000 obscure bots. Each obscure bot uses the Pareto distribution with mean 20 and scale parameter 1.01 to generate the number

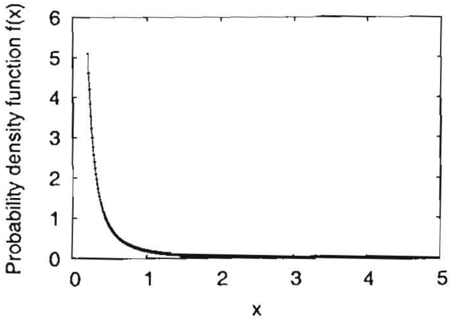


Figure 3. PDF of Pareto distribution

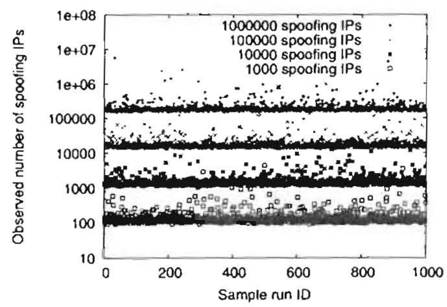


Figure 4. Observed spoofing IPs

of spoofing IP addresses. For each scenario, we simulate 1000 times. The results are shown in Figure 4, where each data point represents the number of observed spoofing IPs. It is noted that for each scenario, the number of observed spoofing IPs is highly clustered among the 1000 sample runs. Suppose that the adversary has observed 3000 spoofing IP addresses. Then, he can infer that the real size of the botnet is likely to lie between 10000 and 100000. In the design of RatBot, we thus use another level of obfuscation (i.e., parameter-level obfuscation) to defeat such kind of statistical inferences.

In the following, we establish the relative error of the adversary's estimate on the botnet size:

Proposition 1 *Consider a RatBot botnet which has n bots. In this botnet, the fraction of obscure bots is ξ and n' spoofed IP addresses are generated. Suppose that through monitoring, the adversary knows both the exact number of explicit bots and the sum of the numbers of obscure bots and spoofed IP addresses. Then, the relative error of his estimation on the botnet size e is bounded as follows: $\xi \leq e \leq n'/n$.*

Proof. Let $\hat{n}$ denote the adversary's estimate on the botnet size. Obviously, $(1-\xi)n \leq \hat{n} \leq n' + n$. We can thus derive the relative error of his estimation as in the proposition. □

From the proposition, we know that high values of ξ and n' help increase the low and upper bound of the relative error, respectively.

6 Kad-Based RatBot Implementation

In this section, we discuss how to implement RatBot based on KAD, which extends from the Kademlia protocol proposed by Maymounkov and Mazieres [18]. We refer interested readers to the literature [18, 6] for more details about Kademlia and KAD. Our implementation of RatBot is based on a popular KAD client, *aMule*[2]. UDP is used in aMule for searching and publishing data objects. If it is an explicit bot, we keep the original implementation intact. Otherwise if it is an obscure bot, we make the following modifications. First, when the bot receives a request message, it drops the message immediately. A request message in KAD carries some special operation codes, such as `KADEMLIA_HELLO_REQ`, `KADEMLIA_SEARCH_REQ`, `KADEMLIA_REQ`, `KADEMLIA_PUBLISH_REQ`, etc.

Second, in the KAD protocol peers regularly send `KADEMLIA_HELLO_REQ` messages to each other to exchange liveness information. It is noted that the adversary can use such messages to determine whether a peer is an obscure bot or just a spoofed IP address. There are two solutions to this. One option is that the obscure bot obfuscates these messages as well, using spoofing IP addresses. The flip side of this approach is that peers may inject those spoofed IP addresses into their routing tables, thus affecting normal routing operations. The other solution is that an obscure bot does not send out such messages at all. Even though obscure bots and their spoofed IP addresses may still be inserted into their neighbors'

[2]The version we used in our study is aMule 2.1.3.

routing tables when their neighbors receive search requests from them, the lack of liveness messages makes them less likely to be chosen in a search process because KAD prefers long-lived nodes when forwarding search requests. Also, when a peer node finds that a neighbor has not been alive for a certain period of time, it removes that neighbor from its routing table. Given these considerations, we adopt the second approach in our implementation.

Third, as obscure bots do not send out `KADEMLIA_HELLO_REQ` messages to their peers, their peers do not send back response messages with type `KADEMLIA_HELLO_RES`. According to the standard KAD protocol, obscure bots' routing tables would shrink faster because neighbors without liveness messages are removed from the routing table after a certain period of time. To avoid this, we increase the longevity of each neighbor without liveness messages in an obscure bot's routing table from the original two minutes to two hours.

Fourth, when an obscure bot initiates a search operation with key $\mathcal{K}$ at time t, it acts as discussed in Section 4.3. The distributions Γ and Ψ are obtained by running some random searches. A possibility for the contact repository $\mathcal{R}$ can be the neighbors that are in the routing table. The problem for this approach is that not all these neighbors have been contacted in the past authentic search sessions. To make spoofing search sessions mimic authentic search sessions, we maintain a separate contact list at each obscure bot. The list records the last 50 contacts (not necessarily unique) used in authentic search sessions. When an obscure bot tries to obtain a contact in a spoofed session from $\mathcal{R}$, it uses that contact list to derive the frequency histogram of each contact on it and randomly chooses a contact based on the empirical frequency distribution. Also, an obscure bot orders request packets in a spoofing session with search key $\mathcal{K}$ according to the XOR metric distance between the recipient of the request packet and $\mathcal{K}$. This is because in a KAD search operation peers are recursively requested until their IDs get close to the ID of the requested object.

Fifth, it is noted that a KAD node initiates some random searches when it observes that a bucket does not have enough contacts in its routing table. For an obscure bot, it has to use its authentic IP address for such random lookups. It is necessary to obfuscate these searches also, because otherwise the adversary can infer whether an observed IP address is authentic or not by how many unique keys it uses for searching. In our implementation, we obfuscate these random searches as well in a similar fashion.

Finally, we let RatBot use the metadata tags in KAD, such as filenames, to hide C&C information. Hence, no data transfer is needed for normal bot operations. Also, obscure bots never publish any information into the P2P network; they only passively search commands given from the botmaster. The botmaster uses only explicit bots to publish his C&C information. It is worth noting that this implementation has some implications. In some circumstances, the botmaster wants to collect certain information (i.e., credit card information on compromised machines) harvested by each bot. As the KAD-based RatBot does not allow obscure bots to publish information, these bots have to use other communication channels instead of the P2P network itself to send back information requested by the botmaster. For instance, the botmaster can specify a data collection server or an email address in the C&C message to which each bot should report.

7 Experimental Evaluation

We now evaluate the effectiveness of RatBot in preventing the adversary from obtaining an accurate estimate on the botnet size. Due to the destructive nature of RatBot, we do this in a simulated environment to avoid legal and ethical issues. As mentioned earlier, our KAD-based implementation of RatBot used the actual implementation code of aMule. We further intercepted all system calls in it, such as time-related and socket functions and replaced them with simulated function calls specific to our local distributed simulation platform. According to the literature, behaviors of both normal P2P users and bots exhibit strong time zone effects [25, 8]. To incorporate these details into our simulation, we

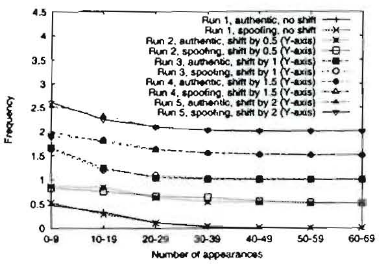
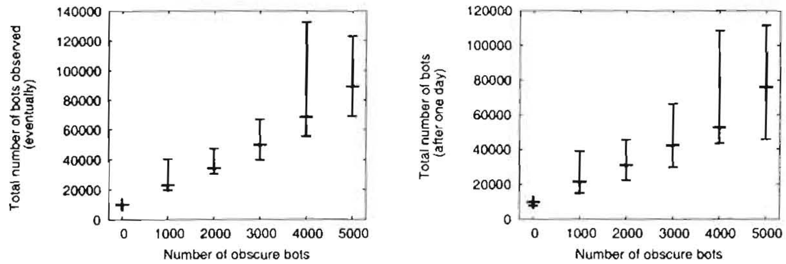


Figure 5. Frequency histogram of the number of appearances in five runs



(1) Eventual results

(2) One-day results

Figure 6. Total number of bots observed by the monitors, including explicit, obscure, and spoofing bots

model the geographic distribution of normal KAD peers based on previous measurements on the KAD network [25] and that of bots according to the Storm botnet IP distribution [5].

Our model of normal P2P user behaviors is based on the observations on the online patterns of normal KAD users [24]. The starting time of a normal peer being online is modeled with a Gaussian distribution with mean at 7:00pm and standard deviation at 2 hours, and the duration of an online session is generated with a three-parameter Weibull distribution. The online activity model of a bot machine is simply defined as follows: the starting time of it being online is drawn from a Gaussian distribution with mean at 8:00am and the end time is drawn from a Gaussian distribution with mean at 6:00pm; for both distributions, the standard deviation is one hour. This model reflects people's normal work hours.

The number of spoofing IP addresses corresponding to an obscure bot is generated from a Pareto distribution whose parameters are set as follows. Let us number the 24 time zones from 1 to 24. The mean of the Pareto distribution is drawn from a Gaussian distribution with mean and standard deviation set as $2z$ and $4z$, respectively, where z is the time zone number of the obscure bot. The scale parameter of the Pareto distribution is 1.05 and its cutoff parameter can be calculated accordingly from its mean.

7.1 Exclusive RatBot

In the first set of experiments, we study the behavior dynamics of exclusive RatBots. We let the botmaster send out a command every day. To improve the reachability of the command to individual bots, the botmaster uses five bots to publish it with 32 keys[3] periodically every 100 seconds. Each individual bot, when online, periodically searches the command every 100 seconds with these 32 keys until it gets the command successfully. In the experiments, we simulate 10,000 bots and vary the number of obscure bots among $\{1000 \times i\}_{i=0,1,2,3,4,5}$. Among the 10,000 bots, 10% of them are P2P servers that always stay online. We assume a strong adversarial model in which the adversary controls 10 servers that can be used to monitor bot traffic. We simulate the botnet for two days: the first day is used as a ramp-up phase for each obscure bot to obtain some empirical distributions, and the second day is used for testing. For each scenario, we simulate it for 20 times with different random number seeds.

We first verify our implementation to ensure that behaviors of spoofing sessions are close to those of authentic sessions. In Figure 5, we depict the frequency histogram of the number of appearances of packets from spoofing and authentic sessions observed by the monitors, respectively, in five runs when there are 1000 obscure bots. There is no obvious systematic difference between authentic and spoofing sessions that can be exploited to differentiate them. From the simulation results, we also note that

[3]We use 32 keys here to mimic the behavior of Storm botnet.

regardless of the number of obscure bots in the RatBot, almost every individual bot gets the command eventually. Hence, the existence of obscure bots does not affect the utility of the P2P botnet.

Figure 6 gives the median, smallest, and largest number of IP addresses observed by the adversary in 20 sample runs eventually and after one day, respectively, under different number of obscure bots. In the eventual results, we show the total number of spoofing IP addresses generated by obscure bots plus the number of actual bots. We notice that after one day, the adversary observes a large fraction of both actual and spoofing IP addresses. This is because we assume a strong adversarial model where the adversary is able to deploy monitors among the core servers of the P2P botnet and the bots search the command frequently.

Unsurprisingly, if we increase the number of obscure bots, the number of observed IP addresses by the adversary also increases. When there are 4000 or 5000 obscure bots, there are cases where the total number of IP addresses observed by the adversary exceeds 100,000, suggesting that the obfuscation technique of RatBot can lead to an overestimation more than 10 times of its actual size. On the other hand, given the same number of obscure bots, the observed number of IP addresses also varies significantly among different runs. In some scenarios, the largest number of IP addresses observed is twice as much as the smallest number of IP address observed in the 20 sample runs. It is also noted that the median tends to be close to the minimum due to the fact that the Pareto distribution is skewed towards its cutoff parameter at its lower end.

7.2 Immersive RatBot

In the second set of experiments, we evaluate how immersive RatBot affects the accuracy of botnet size estimation. We simulate a P2P network with 7,000 normal peers and 3,000 bots. The botmaster users five bots to publish commands with 32 keys periodically every half hour. Each bot uses these 32 keys to search for the current command every half hour until it obtains the command successfully. Here, we let bots perform publish and search operations less frequently than those in exclusive RatBot because normal P2P peers may treat these bots performing frequent operations as abnormal and thus limit interations with them. Among 7,000 normal peers, 990 of them always stay online as servers. We assume the adversary deploys 10 monitors in the network and they appear as servers always online. Each monitor is also a captured bot and can be used to reveal the 32 keys used by the bots to search the current command. The monitor identifies a peer as a bot if it observes that the peer uses any of these keys to search or publish a data item in the P2P network.

We vary the number of obscure bots among 0, 1000, 2000, and 3000 in the experiments. For each scenario, we simulate it for four days, the first of which is used as a ramp-up phase for each obscure bot to obtain some empirical distributions and the remaining days are used for testing. We simulate each scenario 20 times with different random number generation seeds.

In the experiments, we observe that all the bots were able to obtain the command correctly, suggesting that the existence of obscure bots does not affect the normal operation of the P2P botnet. Figure 7 depicts the number of bots observed by the adversary under different numbers of obscure bots. For visual clarity, we shift the points horizontally slightly to prevent overlapping. For each scenario, we show the median, minimum, and maximum among the 20 sample runs. The results corresponding to "Eventually" show the sum of both the number of authentic bots (including obscure bots) and the total number of spoofing IP addressed generated by all obscure bots.

According to the results, we make the following observations. First, the existence of obscure bots produces estimated botnet sizes with high variation. For instance, after three days, if there are no obscure bots, the ratio of the maximum and the minimum of observed bots is 1.016; when we introduce 1000, 2000, and 3000 obscure bots, the ratio becomes 3.405, 2.637, and 2.006, respectively. Such high variation renders it difficult for the adversary to infer the true size of the botnet. Second, it is obvious

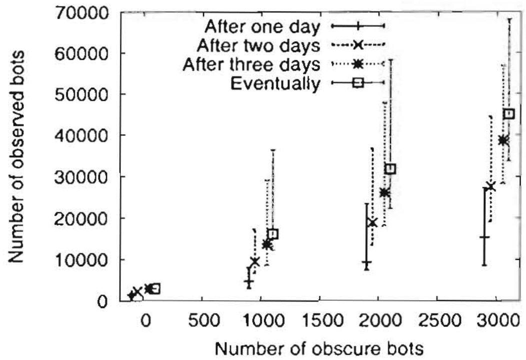


Figure 7. Number of bots observed by the monitors under different numbers of obscure bots (0, 1000, 2000, 3000)

that increasing the number of obscure bots helps inflate the number of observed bots by the adversary. When there are 1000 obscure bots, the ratio of the median number of observed bots after three days to the true size of the botnet is only 4.5, but when there are 3000 obscure bots, this number becomes 12.8. Hence, the botmater can use the fraction of obscure bots in the network to control how much error the adversary's estimate of the botnet size can have.

8 Countermeasures

In this section, we present a few countermeasures that can potentially defeat the obfuscation techniques deployed by RatBot. First, RatBot requires each bot to contact a central server to decide whether it should work as an obscure bot. The server can easily become a single point of failure, unless the botnet applies advanced fast-flux techniques to improve its resilience. If the adversary manages to monitor traffic from and/or to this server, the identities of true bots can be revealed.

Second, in order for RatBot to operate, the search operation must be spoofable. Hence, if a P2P network deploys anti-spoofing techniques, RatBot cannot survive in it. For example, the P2P network can simply use TCP for all signaling and data transfers. Even if UDP is used for signaling, the P2P network can add a level of anti-spoofing mechanism in a query: when Peer A receives a query from Peer B, it sends back a confirmation request to Peer B and only answers Peer B's query after receiving a reply from Peer B on its request. It is noted that this countermeasure works only against immersive RatBot because the botnet has to be blended into an existing P2P network.

Third, if the RatBot needs TCP data transfer to fetch the command, the adversary can deploy monitors in the P2P network and place those command data on them. By monitoring which machines fetch the command data, the adversary can obtain a list of authentic bots as the three-way handshaking mechanism in TCP cannot be spoofed with spurious IP addresses.

Fourth, another effective approach to defeat RatBot is deploying anti-spoofing techniques in the whole Internet. The degree to which the RatBot can obfuscate its size depends on how many obscure bots it has to perform spoofing operations. If the majority of Internet addresses cannot be spoofed, we can still obtain a good estimate on the size of RatBot by simply ignoring those obscure bots.

9 Conclusions

The latest generation of botnets has adopted the P2P structure to improve their resilience against a single point of failure. A number of efforts have been dedicated to estimating existing P2P botnets such as the Storm botnet. In this work, we explore the strategies that an attacker may have to obfuscate the sizes of P2P botnets. We hope our work will raise the awareness of white-hat practitioners on the challenges of estimating the sizes of P2P botnets accurately and adopt effective countermeasures in practice.

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