Blacklists Assemble: Aggregating Blacklists for Accuracy

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***Abstract*—IP address blacklists are a useful defense against various cyberattacks. Because they contain IP addresses of known offenders, they can be used to preventively filter unwanted traffic, and reduce the load on more resource intensive defenses. Yet, blacklists today suffer from several drawbacks. First, they are compiled and updated using proprietary methods, and thus it is hard to evaluate accuracy and freshness of their information. Second, blacklists often focus on a single attack type, e.g., spam, while compromised machines are constantly and indiscriminately reused for many attacks. Finally, blacklists contain IP addresses, which lowers their accuracy in networks that use dynamic addressing.**

We propose BLAG, a sophisticated approach to select, aggregate and selectively expand only the accurate pieces of information from multiple blacklists. BLAG calculates information about accuracy of each blacklist over regions of address space, and uses recommendation systems to select most reputable and accurate pieces of information to aggregate into its master blacklist. This aggregation increases recall by 3–14%, compared to the best-performing blacklist, while preserving high specificity. After aggregation, BLAG identifies networks that have dynamic addressing or a high degree of mismanagement. IP addresses from such networks are selectively expanded into /24 prefixes. This further increases offender detection by 293–411%, with minimal loss in specificity. Overall, BLAG achieves high specificity 85–89% and high recall 26–61%, which makes it a promising approach for blacklist generation.

I. Introduction

Compromised devices are constantly being drafted into botnets and misused for attacks, such as sending spam and phishing emails [72], scanning for vulnerabilities, participating in denial-of-service attacks [27], [32], [85], and spreading malware [80]. *IP blacklists* ("blacklists" for short), which contain identities of prior known offenders, can be helpful as the first-layer defense. Assuming that prior offenders are likely to reoffend, filtering traffic from blacklisted sources can proactively prevent recurrent attacks. It also helps during high-volume attacks, such as denial of service or worm spread, because it reduces load on more resource-intensive defenses, such as network intrusion detection systems [69] and DDoS scrubbers [13]. Blacklists are widely used by network providers [45] and researchers [68], [73], [76], [84], but they have several drawbacks, which we seek to address in this paper.

Blacklists are created by organizations, which monitor some regions of the Internet for specific malicious activities. This limited observation introduces two deficiencies. First, blacklists are often attack-type-specific and will miss offenders who engage in a different malicious activity (e.g., a spam blacklist will contain known spammers but not known booters). On the other hand, compromised hosts are traded on black market and reused for many malicious activities [53], [80], [82], [88], indiscriminately and consistently. A host, which sends spam today could engage in DDoS or spread ransomware tomorrow. Thus, it would make sense to create generic blacklists, which aggregate information from attack-type-specific lists, to increase offender detection. Second, blacklists accuracy may vary a lot. A blacklist may miss certain attacks, because they occur in parts of the Internet that the blacklist's maintainer cannot observe (e.g., a US-based spam blacklist, created by analyzing e-mails on a large mail server, may miss spam attacks launched by Chinese hosts on Brazilian users). A blacklist may also miss observable attacks, or falsely list legitimate addresses, depending on the tuning of its detection algorithm. Thus, each blacklist will have portions of accurate information, which we would want to include in aggregation, and portions of inaccurate information, which we would want to exclude. To achieve such selective aggregation, we need a way to identify regions of the Internet address space where a given blacklist performs well or poorly. Third, blacklists may miss offenders or falsely filter legitimate traffic due to dynamic addressing [56], [65], [68]. Blacklists are also reactive, and will miss new offenders from networks that have historically harbored offenders in the past [88]. We would like to identify such dynamic and mismanaged networks, where we can replace blacklisted addresses with prefixes to improve offender detection. We would also like to perform such expansion *selectively*, i.e., only when it does not lead to large increase in false positives.

In this paper we propose BLAG, a sophisticated blacklist aggregation approach, which addresses the problems we outlined. BLAG aims to increase recall (rate of offender identification or true positives) over individual blacklists, while maintaining high specificity (low rate of false identification or false positives). BLAG has three novel contributions, compared to prior work on blacklist aggregation [78], [84].

1) It uses an estimate of false positives (specificity) over different blacklists and IP-address regions to identify

areas of blacklists to aggregate. This increases specificity of the aggregated master blacklist by 3.9–10.9%, when compared with naive aggregation of all blacklists.

2) It uses recommendation systems to overcome information sparsity problem in blacklists. This helps BLAG rely on good reputation of some blacklists to boost weak signals and increase recall. BLAG improves offender detection accuracy by 3.3–14.3% over individual blacklists.
3) It evaluates each region of Internet address space for dynamic addressing or mismanagement. If either is found, BLAG may replace the addresses from the region with /24 prefixes, if anticipated loss of specificity is acceptable. This *selective expansion* further improves recall, by 411% with a maximum of 14% loss in specificity.

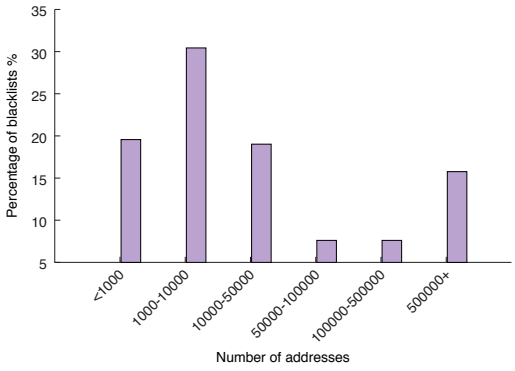
BLAG outperforms naive aggregation of all monitored blacklists, and achieves higher specificity while increasing recall by 226%. BLAG also outperforms PRESTA [84], a recently proposed blacklist aggregation approach by achieving 107–402% higher specificity than PRESTA.

II. Datasets, Metrics and Use Cases

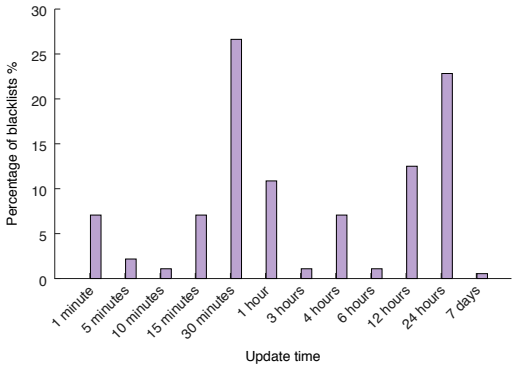
To illustrate the problems experienced by the current blacklists, we have analyzed 184 publicly available blacklists, collected regularly over a one-year period. We have further collected several ground-truth datasets containing known-legitimate and known-malicious traffic sources. We use these datasets to evaluate performance of current blacklists and to evaluate BLAG. We describe our datasets and metrics in this section, and discuss performance goals and blacklist use cases.

A. Datasets

Black. This dataset provides input into BLAG and competing approaches. We have collected 184 publicly available blacklists continuously for 13 months starting from January 2016 to February 2017. Each blacklist may be updated at a different frequency by its provider, ranging from 15 minutes to 7 days. The distribution of update times for our dataset is show in Figure 1(b). Our collection algorithm detects the update frequency for each blacklist and refreshes its snapshot regularly. We have collected around 176 million blacklisted addresses over 23,483 autonomous systems. Our blacklist dataset is representative of different attack vectors such as spam, malware, DDoS attacks, ransomeware, etc. Table I shows the blacklists maintainers roughly classified into four categories based on the attack type they monitor and the number of blacklists maintained by them. Our dataset includes popular blacklists such as DShield [60], Nixspam [67], Spamhaus [44], Alienvault [1], Project Honeypot [38], Abuse.ch [48], Emerging Threats [18] and malc0de [30]. Figure 1(a) shows the blacklist size distribution in the dataset. On one hand, we have large blacklists (15.76%) listing more than 500,000 addresses and on the other, we have small blacklists (19.56%) which list less than 1,000 addresses.



(a) Size of blacklists



(b) Update times of blacklists

Figure 1: Blacklist size and update times.

Ground truth: Mailxam (Mailinator+Alexa+Ham). This dataset contains one source of malicious addresses and two sources of legitimate addresses, collected over the same month of June, 2016. Simultaneous collection is important, because an address may be malicious at one time, and cleaned afterwards. Our malicious source comes from **Mailinator** [29], a service, which allows users to redirect unwanted e-mails to a public inbox. We filter e-mails from these public inboxes during June 2016, using Spam Asssassin [66] to obtain around 2.3 M spam e-mails, sent by around 393 K addresses. These addresses form our malicious dataset. Our first source of legitimate addresses are **Alexa**'s [26] top 500 K websites mined in June 2016. Out of this set we remove websites that may host malware, using Google Safe Browsing API [61] for detection. Afterwards, we convert the domain names into addresses using DNS, which leaves around 284 K addresses. Our second source of legitimate addresses, **Ham**, comes from our human user study. This study was reviewed and approved by our IRB. We recruited 37 volunteers, who allowed us automated access to their GMail inbox, during June 2016. We scanned each participant's GMail account using a plugin, which we developed. Our plugin used OAuth2 protocol to access GMail without requiring the participant's GMail credentials, and it used regular expressions to extract a sender's address, time and label for each e-mail. The label in GMail can be assigned by a user

Type	#	Blacklist Maintainers
Malware	51	Emerging threats [19], Malware Bytes [21], Clean MX [11], Jigsaw security [25], CyberCrime [15], Swiss security blog [48], Bambenek [5], NoThink [35], I-Blocklist [22], NoVirusThanks [36], DYN [23], Malc0de [30], Malware domain list [31], Cyber Threat Alliance [14], Botscout [51], ASProx Tracker [2]
Reputation	49	Emerging threats [19], Graphiclineweb [24], Alienvault [1], Binary Defense Systems [6], CINSscore [9], Swiss Security Blog [48], Blocklist.de [7], I-Blocklist [22], Cisco Talos [10], Bad IPs [4], Blocklist Project [52]
Spam	48	Spamhaus drop and edrop [44], Stop Forum Spam [47], Chaosreigns [3], Lashback [28], Nixspam [67], Project Honeypot [38], Sblam! [41], Turris [20], Malware bytes [21], Cleantalk [12], My IP [33], Pushing inertia [39], BadIPs [4]
Attacks	36	I-Blocklist [22], Malware Bytes [21], Snort Labs [43], Jigsaw Security [25], TrustedSec [49], Haley [8], Darklist [17], SIP blacklist [46], VoIPBL [50], DShield [60], NoThink [35], OpenBL [37], Cruzit [42], BruteforceBlocker [16], Clean MX [11], Bad IPs [4], MaxMind [40]

Table I: Four types of blacklists, roughly categorized by the type of malicious activities they capture. Each row gives the number of blacklists and blacklist maintainers for that type.

Dataset	Start time	Type	Sources
Mailxam	06/01/2016	Malicious	Mailinator (393 K)
30 days		Legitimate	Alexa (284 K)
		Legitimate	Ham (45 K)
Miraixa	09/01/2016	Malicious	Mirai (232 K)
31 days		Legitimate	Alexa (330K)
Darkexa	02/01/2017	Malicious	Darknet (3.9 M)
16 days		Legitimate	Alexa (281K)

Table II: Ground-truth datasets used in this study, collected in 2016/2017.

or by GMail and it is usually "spam", "inbox" or a user-defined label like "conference". We harvested information only from e-mails that have labels other than "spam". Our scanning generates as output a list of {sender IP address, time} tuples, which we save. We collected no identifying information about our study participants, thus this collection posed no privacy risk. We extracted around 178 K e-mail records, sent by around 45 K addresses.

Ground truth: Miraixa (Mirai+Alexa). This dataset contains one source of malicious and one of legitimate addresses, both collected during September 2016. Our malicious source comes from Netlab's [34] scans of **Mirai**-infected hosts during September 2016. There were around 232 K infected hosts. Our legitimate source comes from **Alexa**'s top 500 K websites, mined in September 2016, and filtered as described for the previous dataset. We collected around 330 K legitimate addresses.

Ground truth: Darkexa (Darknet+Alexa). This dataset contains one source of malicious and one of legitimate addresses, both collected in February 2017. The malicious source comes from sources of TCP scans (SYN packets) sent to CAIDA's /8 **Darknet** [57] in February 2017. These sources may be spoofed, but we have no way to identify and remove spoofed scans. We collected around 3.9 M malicious addresses. Our legitimate source comes from **Alexa**'s top 500 K websites, mined in February 2017 and filtered as described for previous datasets. We collected around 281 K legitimate addresses.

Our three datasets contain sources of diverse attacks: spam, DDoS or vulnerability scans. This allows us to test how well BLAG could prevent these attacks if used to filter traffic to a deploying network.

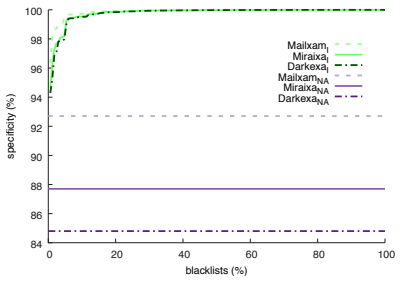
Limitations. Our datasets suffer from several limitations. The Black dataset contains only the publicly available blacklists, while many providers also offer for-pay blacklists that may be larger and more accurate. We chose to use only the public blacklists because: (1) these blacklists are widely used and we wanted to evaluate BLAG's benefits for an average user, (2) we wanted our work to be repeatable, and using public blacklists enables us to freely share our data. We plan to share all the datasets from this section and our BLAG blacklist by the final version deadline. We believe that BLAG's benefits would carry over to for-pay datasets, because its mechanism is generic.

Another limitation is that legitimate and malicious datasets are small and imperfect. They only capture a sample of legitimate/malicious addresses that were active in the Internet at a given point in time and for a given legitimate or malicious purpose. We also rely on other security technologies, such as Google safe browsing or SpamAssasin to label an address as legitimate or malicious at a given point in time. These limitations are present in other published works [59], [63], [71], [78], [84], [87], which use similarly-sized malicious and legitimate datasets, and rely on secondary technology, as do we, to establish maliciousness at a given time. These limitations cannot be avoided, as there is no complete, 100% accurate list of legitimate and malicious addresses in the Internet nor in any specific network, at any given point in time.

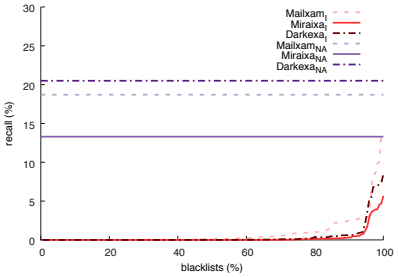
Our datasets contain addresses of different types. For example, in Miraixa, malicious addresses belong to IoT devices, while legitimate addresses belong to Web servers. This is not a limitation. Internet traffic contains a variety of hosts, which engage in a variety of behaviors. Our datasets contain a small subset of these hosts and behaviors, where we could establish legitimacy or maliciousness, with some degree of confidence. They are not perfect, but we hope they are sufficient to provide a common ground truth to evaluate BLAG and competing approaches.

B. Metrics

We measure performance of blacklists using *recall* and *specificity*. Recall measures the percentage of offenders (out of some ground-truth set) that were blacklisted. Specificity measures the percentage of legitimate hosts (out of some ground-truth set) that were not blacklisted.



(a) Specificity



(b) Recall

Figure 2: Blacklist specificity is usually high but recall is low. Naive aggregation (denoted by NA) has higher recall, but with lower specificity.

C. Use Cases and Performance Goals

Performance goals for any given blacklist depend on when and how it is used. If a blacklist is used *preventively*, as a first-layer defense, and is on all the time, it is very important that the blacklist has high specificity. This is to ensure that no legitimate traffic is regularly dropped. Current blacklists have high specificity (near 100%) but extremely low recall. If a blacklist is used *reactively*, to prioritize traffic drops during a high volume attack, such as DDoS or a worm infection, it is very important to maximize recall, and achieve some reasonably high specificity. Our work targets this second use case. We will show in Section V that BLAG achieves more than 86% specificity, while significantly increasing recall, compared to individual blacklists.

III. Problems With Current Blacklists

In this section we illustrate the problems that blacklists have and that we aim to handle. To estimate specificity and recall for individual blacklists, we calculate the *daily* overlap between addresses reported in the malicious and legitimate sources for Mailxam, Miraixa and Darkexa datasets and the addresses reported by the individual blacklists. We then report the total percentage of legitimate (specificity) and malicious (recall) addresses listed over the course of the entire ground-truth dataset.

We first show that all blacklists have generally high specificity but poor recall. This motivates the need for their aggregation. We further show that naive aggregation fails. It increases recall but severely lowers specificity. We show that this occurs because each blacklist's specificity varies a lot spatially, i.e., over regions of IPv4 address space. This motivates us to identify and aggregate only those portions of blacklists that have high specificity. Finally, we discuss that dynamic addressing and network mismanagement are prevalent, which warrants representation of some blacklist information as network prefixes instead of addresses. This argument is supported by observing high filling degree or spatio-temporal utilization (defined by Richter et al. [74]) in networks monitored by blacklists.

A. Missed Attacks and Naive Aggregation

Individual blacklist's specificity is shown in Figure 2(a) and recall in Figure 2(b), for our three datasets. Specificity is generally high ($> 94.2\%$), which means that no individual blacklist will erroneously list many legitimate sources. Recall on the other hand, is generally low. The best recall a blacklist from our Black dataset had was 13.5% on Mailxam, 5.6% on Miraixa and 8.4% on Darkexa. Previous blacklist studies have similarly observed high specificity and low recall [77].

One approach to improve recall is naive aggregation of blacklists. Naive aggregation would include every address ever seen on any blacklist into a *historical blacklist*. We show how this naive aggregation would perform on our ground-truth datasets with regard to specificity (Figure 2(a)) and recall (Figure 2(b)) with a horizontal bar. Naive aggregation has higher recall than any monitored blacklist. About 18.7%, 13.3% and 20.5% of malicious addresses from Mailxam, Miraixa and Darkexa datasets are detected for naive aggregation. But naive aggregation has much lower specificity of 92.7%, 87.8% and 84.8% for Mailxam, Miraixa and Darkexa datasets. The challenge we address in this paper is how to design a smarter aggregation approach, which achieves better recall with minimal loss in specificity.

Implications: Blacklists generally have low recall but high specificity. Therefore, we will aggregate portions of blacklists, which have high specificity, to increase recall.

B. Spatially-Varying Specificity

Blacklist specificity varies across the Internet's address space, because each blacklist observes only some portions of address space, and may have some false positives in what is being observed. To illustrate spatially-varying accuracy, we first combine legitimate addresses from our three ground-truth datasets into networks, where a network is /24, /16 or the autonomous system (AS). We then calculate for each blacklist the percentage of the networks where a blacklist has lower-than-100% specificity, i.e., where using this blacklist would inflict some collateral damage. About 82% of blacklists have specificity lower than 100% only in 2% of legitimate /24 prefixes in our ground-truth datasets. Percentage of networks where a blacklist is inaccurate increases for larger network sizes. As much as 44.4% of blacklists have specificity lower than 100% in more than 10% of the /16 networks, and about 36.5% of blacklists have specificity lower than 100% in more than 10% of

the ASes. In BLAG, we leverage this finding to identify portions of blacklists where information is accurate, i.e., it will not bring a false positive to the deploying network. Only these portions will proceed to aggregation.

Implications: Blacklist accuracy varies across the Internet's address space. Therefore, we aim to devise an approach that can identify areas where a blacklist is very accurate and include listings only from those areas in aggregation.

C. Address Volatility

Blacklists list IP addresses. But in networks that use dynamic addressing, an offender's address can change over time. There are many dynamically-addressed networks today which may affect the performance of blacklists. Thomas et al. [81] observed that devices using Google services are assigned an average of 20 addresses over two weeks. Dynamic nature of addresses was also observed in [56], [65], [68], [74], which estimate dynamic addressing to be prevalent in 8–20% of the Internet.

Another problem with listing addresses is that blacklists can only be reactive, that is, they catch only previously known offenders. Zhang et al. [88] showed the correlation between network mismanagement and maliciousness – malicious entities are often concentrated in few mismanaged networks. If we could identify such mismanaged networks, blacklists could become proactive in that space, by listing the entire network as soon as a few offenders are detected. We observe a pattern of frequent reoffense from several networks in our Black dataset, which is aligned with findings of Zhang et al. About 99.6% of blacklisted addresses reside in the same /16 prefix, and 82.3% of blacklisted addresses reside in the same /24 prefix, as another blacklisted address.

Implications: Detecting potential dynamic addressing and mismanagement in networks can provide indications where coarser blacklisting can lead to improved recall.

IV. BLAG Design

In this section we present the design of our system – BLAG, which selects accurate information from blacklists and aggregates it. We illustrate the system in Figure 3. We assume some given network wants to deploy BLAG for blacklist aggregation. BLAG starts with a set of recently obtained blacklists (B), and prior blacklist observations (P). Also, BLAG uses some set of known-legitimate senders (L) that generated recent traffic to the deploying network. This set is necessary to estimate specificity of various blacklists from B, and select which portions to aggregate. A university network could form this set, for example, by choosing sender addresses from non-spam messages, addresses from other colleges and universities, addresses of popular Web and DNS servers, etc. BLAG selects some addresses from (B) and (P) to be included in its aggregate master blacklist. Periodically, BLAG updates (P) with information from (B), refreshes (B) with updated listings, refreshes (L) with current known-legitimate senders and recalculates aggregated master blacklist. This process repeats indefinitely.

Our goals for BLAG include:

1) *Evaluate* the quality of each blacklist's information for a given address space. We achieve this by calculating a reputation score for each address and each blacklist, and for each /16 network listed by that blacklist. This score is a function of the blacklist's accuracy in reporting prior offenses from the same address space region, i.e., it is an estimate of the expected gain in recall and specificity, if this portion of the blacklist were included in aggregation. Similar to prior work in PRESTA [84], we also take into account the listing's age, and favor inclusion of offenders that were recently listed. Thus, the reputation score is also the function of the address's history of offense. We describe score calculation in Section IV-A.
2) *Aggregate* high-quality pieces of information into the master blacklist. We use recommender systems to calculate missing reputation scores, i.e., to predict the likelihood of re-offense of an address within or across blacklists. We then use a threshold-based approach on these reputation scores to filter out unreliable information. This process is explained in Section IV-B.
3) *Expand* some addresses into prefixes on the master blacklist to increase recall. We expand those addresses that we believe are dynamically allocated, or addresses that belong to mismanaged prefixes. Our expansion method is also selective – it tries to balance the gain in recall against the loss in specificity, and is explained in Section IV-C.

A. Reputation Scores: Evaluating Quality

BLAG starts its aggregation by first generating a reputation score for each address a and blacklist b. Our reputation score for this listing is a sum of two scores: the *historical offense score* $ho_{a,b}$ and the *safety score* $s_{a,b}$.

$$r_{a,b} = \frac{ho_{a,b} + s_{a,b}}{2} \tag{1}$$

The score ranges from 0 to 1. During the aggregation phase, we multiply the scores by 10, to speed up the convergence of the recommendation system. A higher reputation score indicates that the listed address has a higher probability of re-offense, and the blacklist listing the address has high specificity in the given address region.

Address's history of offense $ho_{a,b}$: Historical blacklist data can be a valuable source to detect potential re-offenders, and previous studies have shown recent offenders are more likely to re-offend [84]. We define historical offense score $ho_{a,b}$ as:

$$ho_{a,b} = \frac{1}{2^{\frac{t-t_{out}}{l}}} \tag{2}$$

where l is a constant, which we set empirically (discussed in Section VI-C), t_{out} is the de-listing (removal) time of a at blacklist b and t is the time when the score is calculated. The exponential factor ensures that the score decays exponentially over time, giving higher weight to

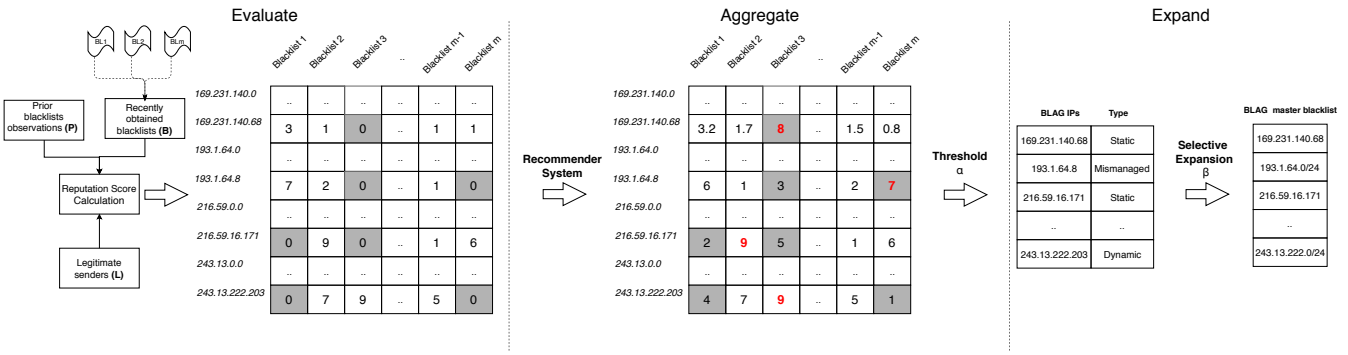


Figure 3: BLAG implementation consists of assigning reputation scores to addresses from different blacklists. Then, recommender system generates scores for addresses, which do not have a score in a given blacklist (shaded blocks). Addresses that have at least one score greater than the α threshold (red numbers) are used for aggregation. These addresses will be put on the master blacklist. Finally, we selectively expand addresses from dynamic or mismanaged networks into /24 prefixes, if we project that this expansion will not severely lower specificity.

recent offenders. If the address a is currently listed in b, we set its historical offense score to 1.

Blacklist's safety $s_{a,b}$: In Section III-B, we illustrated how specificity of a given blacklist varies over the Internet's address space. We capture this dependency in the safety score, with higher values denoting higher estimate of specificity. Let $net(a)$ be a /24 prefix containing address a and $o_{net(a)}$ be the set of all addresses from $net(a)$ that were ever reported in blacklist b. Let e be the set of all listed addresses that are also in (L). We define safety of blacklist b for address a as:

$$s_{a,b} = 1 - \frac{|e \cap o_{net(a)}|}{|o_{net(a)}|} = 1 - \frac{F_a}{|o_{net(a)}|} \tag{3}$$

i.e., the safety of a blacklist is the fraction of the addresses it reports within $net(a)$ that are not misclassifications and F_a represents the number of misclassified addresses in $net(a)$.

B. Recommender System: Calculating Missing Scores

After all the reputation scores are calculated, BLAG places them into a *score matrix* where blacklists are at the columns and listed addresses at the rows as shown in Figure 4. BLAG creates a score matrix for every /16 prefix in the Black dataset. Each cell in the score matrix holds the reputation score $r_{a,b}$ for the given row (address a) and given column (blacklist b). This matrix is very sparse. We fill the empty cells by using a recommendation system. This helps us, in some cases, to elevate low-score addresses on some blacklists, into high-score addresses on other, more reputable blacklists. Such addresses then propagate to the aggregated master blacklist, and help us improve recall without a great loss in specificity.

Recommendation systems are usually used to predict future product ratings by some users, given a set of past ratings of same or related products, by target users and other similar users. A well-known example is the Netflix recommendation system [62], which may recommend a new movie M to user U by relying on the U's past ratings of movies similar to M, and on ratings that users similar to U have given to M or movies similar to M. In our context, addresses are the products that are being evaluated, and blacklists are users assigning the rating. We view the reputation score as the rating.

Two most commonly used recommendation systems are a content-based recommendation system [70] and collaborative filtering [75]. A content-based recommendation system requires explicit definition of features describing the relationship between blacklists and addresses. Such features are hard to obtain, because each blacklist uses proprietary algorithms and private observations to decide when to list an address. We instead use *collaborative filtering*, as it infers information about the relationship between a blacklist and an address using only the existing reputation scores.

Figure 4 illustrates the recommendation system's operation. Let M and N represent the set of addresses and blacklists, respectively. Let R be a score matrix of size $|MxN|$ which consists of reputation scores quantifying the maliciousness of an address being listed by a given blacklist. For example in Figure 4 score matrix R consists of four blacklists ($M = 4$), and five addresses ($N = 5$). Every address need not be present in every blacklist, which makes score matrix R sparse. Address 128.0.0.1 listed in *nixspam* blacklist has a reputation score of 5 (on the scale from 0 to 10). Address 128.0.0.4 has a score of zero in *openbl* blacklist, where it has never been listed. There are latent (unknown) features of blacklists and addresses that lead to an address being listed. Let the number of latent features that influence reputation scores of addresses in blacklists be K (see Section VI-D for how we choose the value of K). Our goal is to estimate the unknown scores in the sparse score matrix R by estimating two matrices $P(|MxK|)$ and $Q(|NxK|)$, which are factors of score matrix R, such that their cross product is approximately equal to known values in R. In other words, matrix factorization is used on R to obtain factor matrices P and Q such that:

$$R \approx P \times Q^T = R' \tag{4}$$

We obtain the values of latent matrices P and Q using

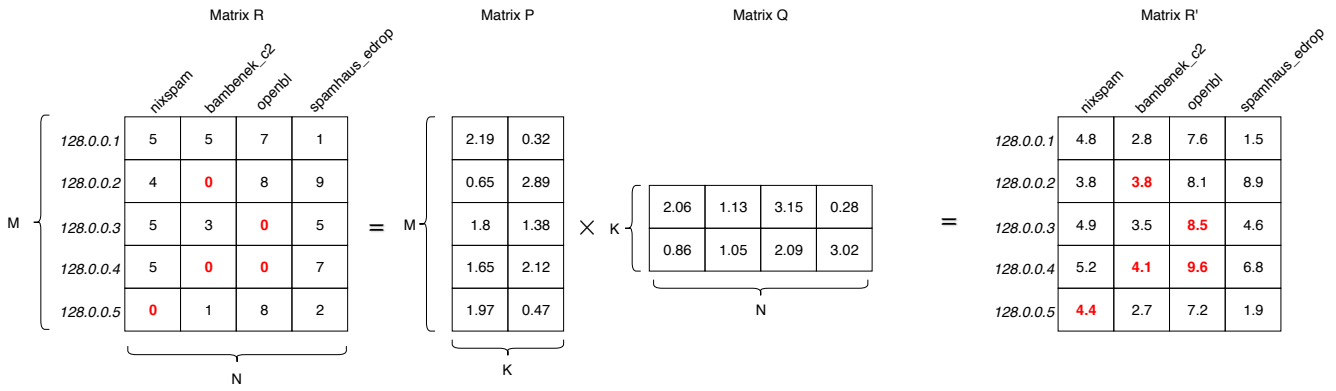


Figure 4: Latent factorization of the score matrix R, a $M \times N$ matrix, where M is the number of addresses and N is the number of blacklists. The cells indicate reputation scores. Addresses not listed in a given blacklist are assigned a zero score. Score matrix is factorized into two matrices of $M \times K$ and $K \times N$, and the cross product results in a new matrix R', which updates the zero score cells with a positive value.

gradient descent [64], which randomly assigns values to P and Q and estimates how different the product of P and Q is from the original score matrix R. We use root mean squared error (RMSE) to estimate the difference. Gradient descent tries to minimize RMSE iteratively. We discuss in Section VI-D the number of iterations required to have a small RMSE.

After obtaining matrices P and Q, each row in P represents the association strength between addresses and latent features K, and each row in Q represents the association strength between blacklists and latent features K. To obtain an unknown reputation score for an address a and blacklist b, the dot product of two latent vectors corresponding to address a and blacklist b is calculated as follows:

$$r_{\text{a,b}} = p_a^T q_b \tag{5}$$

Where p_a defines the association strength of address a with features K and q_b defines the association strength of blacklist b with features K. Consider addresses 128.0.0.3 and 128.0.0.4 in Figure 4, which are not listed in the *openbl* blacklist. Both of these addresses have similar reputation scores in other blacklists (with *nixspam*'s scores of 5 and 5, and *spamhaus_edrop*'s scores of 5 and 7). Intuitively, if these addresses where to be listed in the *openbl* blacklist, we can expect them to have similar scores. Recommendation system captures this pattern. Also *openbl* tends to have a little higher scores for the addresses it lists, compared to other blacklists. This regularity is also captured by the recommendation system. The system generates the R' score matrix, where scores of 8.5 and 9.6 are assigned to addresses 128.0.0.3 and 128.0.0.4 respectively, for the *openbl* blacklist.

After we have calculated all the missing scores, and filled in the empty cells in score matrix R, we proceed to construct the *aggregated master blacklist*. To generate the master blacklist, we observe all blacklists $B = \{b_1, b_2, ..., b_n\}$ and then use a threshold α (choice of α values is discussed in Section VI-E) to include all the addresses a for which the following holds : $\exists b \in B | r_{a,b} \geq \alpha$.

C. Selective Expansion: From Addresses to Prefixes

We have discussed in Section III-C why it would be useful to identify and expand addresses in dynamic and mismanaged networks into address prefixes. Prior work has expanded addresses into prefixes indiscriminately [59], [78], [83] – this improves recall but greatly decreases specificity, as we show in Section VI-A. The novelty of our approach is in first identifying dynamic and mismanaged networks and then expanding addresses belonging to these networks into prefixes, only when this expansion is likely to bring us higher gain in recall than loss in specificity.

The expansion phase starts with master blacklist produced in the previous step, and calculates which addresses could be expanded into their /24 prefixes (see Section VI for rationale behind choosing /24 prefix size). We first generate a list of all /24 prefixes that contain addresses on the master blacklist. We then evaluate if each prefix is either dynamically addressed or mismanaged. On a positive finding, we estimate the recall gain and specificity loss, using our historical offense and safety scores as proxies, respectively. If the estimated gain exceeds the loss, we will include the /24 prefix on the master blacklist.

1) Dynamic Addressing: To determine if a prefix is dynamically addressed we follow the approach proposed by Richter et al. in [74], where the type of addressing in a prefix is determined using sampled logs of traffic passing through Akamai's CDN. Richter et al. define filling degree (FD) as the number of addresses in a /24 prefix, which were active during a monitoring period, and they define spatio-temporal utilization (STU) as the sum of addresses in a /24 prefix, which were active over a duration of time. Richter et al. used observation of traffic in Akamai's logs as proof of address activity. Since we do not have access to such information, and since Richter et al. cannot make their lists of dynamic prefixes public, we use active probing to detect dynamically addressed prefixes.

We conducted active probing of all /24 prefixes that had at least one address in our Black dataset. We probed

Blacklisted	Reachable
1,677,620	1,396,952

Table III: 83.26% of the blacklisted networks had at least one address, which responded to our probes.

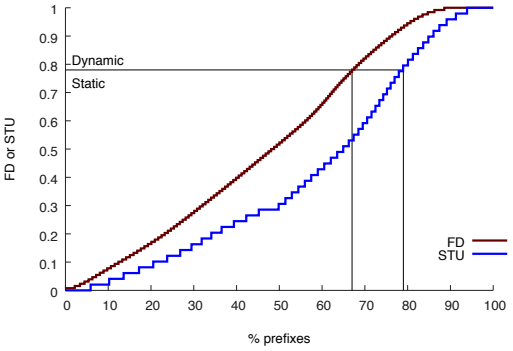


Figure 5: FD/STU of monitored networks.

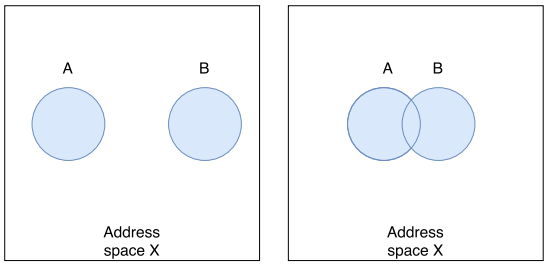
each address every two hours for a duration of one week using ZMap [58]. Table III shows the number of addresses probed and the number of addresses that responded. More than 83.26% of addresses responded to at least one probe. Using these responses we estimate the FD and STU of each prefix, and normalize them by the maximum possible value. We then compare these normalized values to a threshold, to determine if a prefix is dynamically addressed. We consider a prefix p as dynamically addressed if it holds that $max(FD_p, STU_p) \geq 0.78$. We obtain the threshold 0.78 from Richter et al. [74], where more than 90% of dynamically-addressed prefixes have a FD_p or STU_p greater than 0.78. Figure 5 shows the distribution of the normalized FD and STU values for each prefix in our dataset: 67% of the networks are static by filling degree and 79% of the networks are static by spatio-temporal utilization. Thus 33% of networks are dynamic.

During our active probing, 16.7% of prefixes did not respond and thus we must assign them a default label, either static or dynamic. We conservatively adopt the static default label. We observe that both of these labeling approaches perform comparably with regard to recall, but the static label leads to higher specificity.

2) Mismanaged Prefixes: We classify a /24 prefix as potentially mismanaged if it contains more than the threshold N_m addresses, reported by any blacklist. We set $N_m = 2$ (see Section VI-F for rationale).

Type	# of Networks	% of Networks
Only dynamic	312,169	22.4%
Dynamic and mismanaged	148,584	10.6%
Only static	592,829	42.4%
Static and mismanaged	343,370	24.6%
Total	1,396,952	100%

Table IV: Breakdown of probed networks into static, dynamic or mismanaged.



(a) Case 1 (b) Case 2

Figure 6: Different use cases, illustrating how and why BLAG works.

Table IV shows the number of addresses, which are either dynamically addressed or mismanaged or both. About 22.4% of networks are only dynamic networks, 10.6% are both dynamic and mismanaged, 42.4% are only static networks and 24.6% are static and mismanaged. Overall, 57.6% of addresses on our master blacklist are candidates for expansion into prefixes.

3) Selective Expansion: If a /24 prefix is found to be either a dynamic or mismanaged, we selectively expand such addresses into their corresponding /24 prefixes. We estimate the cost of expansion for the /24 prefix a, denoted by SE_a, as:

$$SE_a = 1 - \frac{F_a}{P_a + F_a} \tag{6}$$

where P_a is the number of addresses from address space a, which are predicted to be malicious (i.e., which are included in the BLAG's master blacklist) and F_a is the number of legitimate addresses, which have been historically misclassified as malicious, from Equation 3.

We define a threshold β such that, addresses a which are either dynamic or mismanaged are expanded if $SE_a \geq \beta$. We discuss the choice of β in Section VI-G.

D. Why and How BLAG Works

BLAG assigns reputation scores to addresses listed in blacklists. An address can have a low reputation score when the blacklist listing the address is not safe enough for that address space ($s_{a,b}$ is low) or when the address may not have been recently listed in the blacklist ($ho_{a,b}$ is low) or when both $s_{a,b}$ and $ho_{a,b}$ are low. In such cases, these addresses will have a smaller chance to propagate to the aggregated master blacklist. This may be the right decision in some cases, while in others sparsity of the reputation matrix may impair timely inclusion of repeat offenders on the master blacklist. Recommendation system helps overcome the sparsity problem. We now illustrate with a few toy examples how BLAG works, and how it can achieve smart aggregation. Figure 6 illustrates these cases. For simplicity, imagine that there are only two blacklists reporting address sets A and B in some address region X.

Case 1: Aggregating disjoint listings. Our reputation scores help identify accurate (timely and safe) listings in

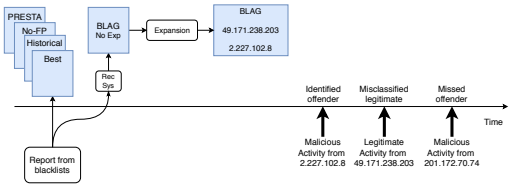


Figure 7: Determining when an address (offender or legitimate) is identified correctly or incorrectly by a blacklist.

A and B. When A and B are disjoint, the recommender system cannot help fill in empty cells. Only addresses that already have a high score in A and B will be included in the master blacklist.

Case 2: Aggregating partially disjoint listings. Our reputation scores help identify accurate listings in A and B. When A and B have some overlap, the recommender system helps fill in empty cells (i.e., those in A but not in B and those in B but not in A). Addresses that already had a high score in A or B will be included in the master blacklist – the recommender system does not influence their inclusion. Other addresses that received a high score by the recommender system (in empty cells of score matrix) but originally had a low score in A or B benefit from the recommender system. They will be included in the aggregated master blacklist, whereas they would have been left out otherwise. In a sparse matrix, many addresses may be influenced this way, and promoted for inclusion. Finally, addresses that received a low score by the recommender system, and that originally had a low score, will be excluded. Recommender system does not influence their exclusion.

As BLAG assimilates more blacklists, the probability of an address matching the case 2 instead of case 1 grows, and we reap benefits from the recommender systems. We evaluate this effect in Section V. Unfortunately, an attacker could misuse the recommender system to pollute our master blacklist. We discuss this effect and possible solutions in Section VIII.

V. Evaluation

In this Section we evaluate the performance of BLAG and several competing approaches, using datasets described in Section II. We find that BLAG achieves reasonably high specificity (≈86%) and high recall (27–61%), while other approaches have either very low recall (<1%), or higher recall but very low specificity (≈33%).

A. Evaluation setup

Competing approaches: We compare BLAG's performance against four approaches:

1) *Best* – the blacklist from Black dataset that performs the best on a given ground-truth dataset with regard to recall; we start with the most recent snapshot of that blacklist prior to the start of the ground-truth dataset and then refresh it with snapshots taken during the ground-truth dataset. *Best* is a hypothetical scenario, because in real deployment we could not tell which blacklist will eventually be the best. It allows us to measure benefits of aggregation over use of a single blacklist.
2) *Historical* – all addresses listed in any blacklist in the Black dataset, up until the end of a given ground-truth dataset. This approach assumes "once malicious, always malicious".
3) *No-FP* – same as historical, but we remove top 10% of blacklists, which contribute the most false positives on the given ground-truth dataset. This is a hypothetical scenario, because in real deployment we could not know which blacklist will contribute false positives. We include it to show that even if we had a way to magically identify low performing blacklists and remove all addresses listed by them, it would still have worse results than BLAG, which aggregates *accurate pieces of different blacklists*.
4) *PRESTA* – the blacklist generated using technique described in [84]. PRESTA performs spatio-temporal analysis and expansion using historical blacklist data to generate a more proactive blacklist. It expands some addresses, which are repeat or recent offenders, into their /24 prefix, and two surrounding /24 prefixes. For example, if the address 1.2.3.4 were chosen for expansion, PRESTA would include 1.2.2.0/24, 1.2.3.0/24 and 1.2.4.0/24 in its blacklist.

Figure 7 illustrates our evaluation methodology. We first take each of our three ground-truth datasets and divide it into seven days of training and the rest is used for testing. We use the legitimate part of the first seven days as our (L) set. During evaluation, for our testing set and for each blacklisting approach (best, historical, No-FP, PRESTA or BLAG) we simulate the dynamics with which the addresses appear over time, both in individual blacklists (Black) and in ground-truth datasets. When an address appears in the Black dataset we:

- include the address in the best blacklist if it appeared on a blacklist, which will ultimately perform the best on the given malicious dataset,
- include the address in the historical blacklist,
- include the address in the No-FP blacklist if the address was not in the top 10% of blacklists, which contributed to false positives in our evaluation. This means we run our evaluation twice for No-FP approach. Once to identify and rank all blacklists that contributed to false positives. They are then removed and we rerun the evaluation. We report the results of this second run.
- apply PRESTA algorithm on the address to determine if it is included in the PRESTA blacklist,
- apply BLAG on the address to determine if it should be included in the BLAG's aggregated master blacklist, and if it should be expanded into its /24 prefix.

Evaluation metrics: In our evaluation we measure recall and specificity for each approach as follows. (1) *Specificity:* When a legitimate address l appears in our testing dataset,

Parameter	Description	Value
l	Length of address history	29 days
K	Number of latent features	3
α	Reputation threshold	8
β	Selective expansion threshold	1
N_m	Mismanaged network threshold	2

Table V: Parameters used in evaluation.

we compare its address against the currently generated blacklist (competing approach or BLAG) at the same point in time in our simulation. If listed on that blacklist, we count l as a false positive. Specificity is the percentage of legitimate addresses that were not false positives. (2) *Recall:* When an offender *o* commits offense in our testing dataset, we compare the offender's address against the currently generated blacklist (competing approach or BLAG) at the same point in time in our simulation. We mark o as true positive if it is currently listed by the blacklist. Recall is the percentage of offenders that are true positives.

Parameter settings: Parameters used in our evaluation are summarized Table V. We set length of address history $l = 29$, number of latent features for recommendation system $K = 3$, number of blacklisted address per prefix $N_m = 2$, reputation threshold $\alpha = 8$ and the selective expansion threshold β*=1*. Our choices for these variables are explained in Section VI.

B. BLAG is More Accurate

The goal of reactive blacklisting is to capture as many offenders as possible, while keeping the specificity high.

BLAG has the best specificity and recall across three traffic datasets: Figure 8 shows that BLAG has overall the best performance. Its specificity is uniformly high, ranging from 85–89% and its recall is higher than that of best, historical and No-FP blacklists. No-FP blacklist has the highest specificity but the lowest recall, indicating that blacklists contributing to higher recall also lower specificity. Best blacklist improves recall but lowers the specificity by 1–6%. Historical blacklist, which is naive aggregation of all blacklist data improves recall by 38–143% when compared with best blacklist but reduces specificity by 7–15%.

BLAG's performance comes both from selection of high-quality data for aggregation and from expansion of addresses into prefixes. We investigated how much of BLAG's performance comes from its selection of high-quality data to aggregate and how much comes from expansion, by showing BLAG with and without expansion (*Exp* and *No Exp* in Figure 8). We compare this performance to performance of best blacklist, and to historical and No-FP blacklists, which perform naive aggregation without expansion.

Even without expansion, BLAG achieves recall, which is always better than best (by 3–14%) and No-FP blacklist (by 56–129%), with a small loss of specificity (up to 6%). Historical blacklists have 20–135% better recall than BLAG without expansion, but lose up to 15% of specificity. Thus, smart aggregation helps BLAG improve recall and specificity over naive and no aggregation approaches. Expansion of BLAG then improves recall further (by 293–411% on our datasets), at a small loss of specificity (up to 14% loss on our traffic datasets). We show in Section VI that, even if we applied selective expansion on other blacklisting approaches, BLAG would still outperform them.

BLAG filters more attacks. Some addresses may generate more attacks than others, i.e., they could be more malicious. We evaluate the amount of malicious activity (e.g., spam, scanning, etc) that would be filtered by BLAG, best, historical and No-FP blacklists for our three traffic datasets. In case of Mailxam dataset, BLAG would filter 61% of spam, compared to 13.5%, 18.7% and 10.2% filtered by best, historical and No-FP blacklists respectively. In case of Miraixa dataset, BLAG would filter traffic from 32.8% of infected devices, compared to only 5.6%, 13.3% and 2.8% filtered by best, historical and No-FP blacklists. In case of Darkexa dataset, BLAG would drop 26% of scans, compared to 8.4%, 20.5% and 5.5% filtered by best, historical and No-FP blacklists respectively.

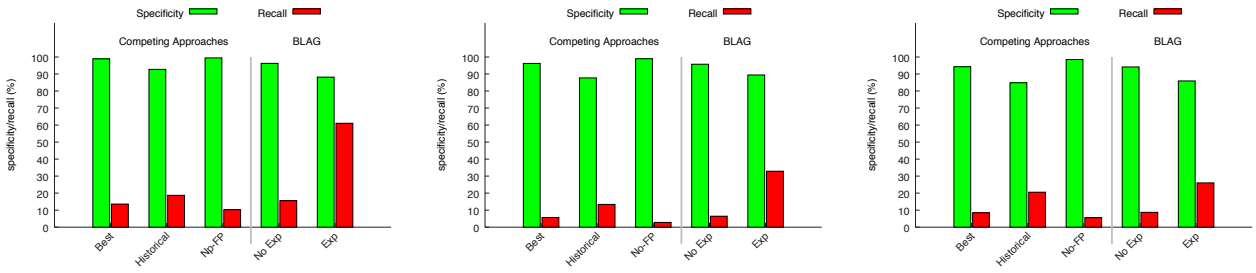
VI. Sensitivity Analysis

In this section we discuss our design choices and values we adopt for constants l, K, α, β and N_m.

A. Expansion Approach

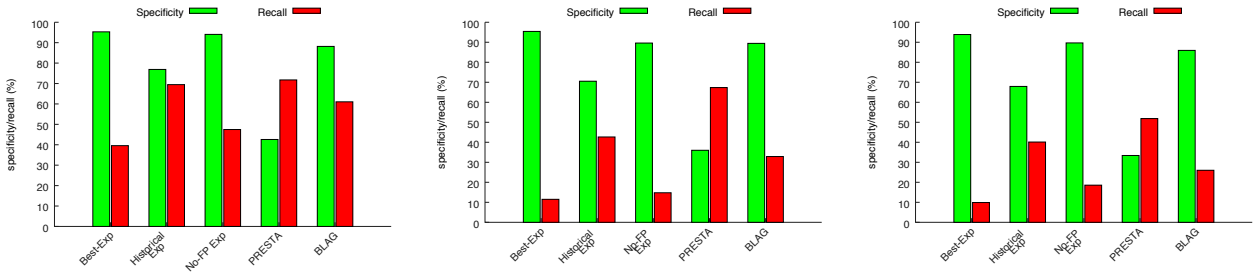
BLAG expands select addresses into /24 prefixes. In this subsection we investigate two questions. First, we ask what if a similar expansion approach to BLAG's were applied to best blacklist, No-FP and historical blacklist. Instead of selective expansion here, which uses BLAG's information, we use regular expansion – each candidate address (mismanaged or dynamic) is expanded into its /24 prefix. We show that BLAG still outperforms competing approaches, due to its selection of only high-quality information to aggregate, prior to expansion. We also compare BLAG with PRESTA, which uses its own expansion technique, and show that BLAG outperforms it. Second, we investigate how BLAG's performance would change if we expanded addresses into their full BGP prefixes or entire autonomous systems.

BLAG outperforms best-expanded, No-FP-expanded, Historical-expanded and PRESTA blacklists. We compare BLAG to best, No-FP blacklist and historical blacklists, with regular expansion and show their performance in Figure 9. Historical expanded blacklists have 13.6%–54.2% better recall than BLAG for all the three datasets, but at the loss of up to 32% of specificity. PRESTA has 17.5–104.8% better recall than BLAG for all the three datasets, at the loss of up to 45.5–53.4% of specificity. BLAG has 54.4–185.8% higher recall than the best-expanded blacklists and has 28.7–122.3% more recall than No-FP-expanded blacklists for all three datasets. BLAG achieves this at modest specificity cost. BLAG loses up to 10.5–14% of specificity, while best-expanded loses 4.6–6.1%, historical-expanded loses 23–32%, No-FP-expanded loses 5.9–10.3%



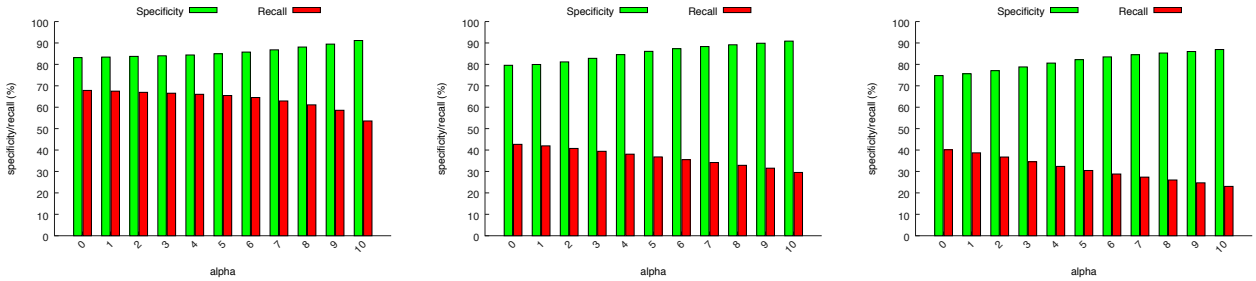
(a) Mailxam (b) Miraixa (c) Darkexa

Figure 8: Specificity and recall of BLAG with three competing approaches on traffic datasets.



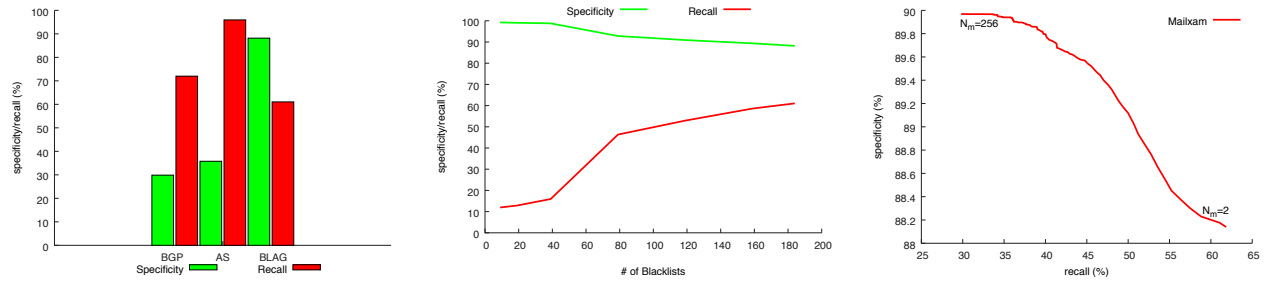
(a) Mailxam (b) Miraixa (c) Darkexa

Figure 9: Specificity and recall of BLAG and four competing approaches with expansion.



(a) Mailxam (b) Miraixa (c) Darkexa

Figure 10: Evaluating α for datasets.



(a) Evaluating expansion (b) Evaluating contribution of blacklists by size (c) Evaluating N_m

Figure 11: Sensitivity analysis on mailxam dataset.

and PRESTA loses 57.4–66.6%. Thus BLAG strikes the right balance between maintaining high specificity and improving recall.

BLAG's expansion approach outperforms expansion at BGP prefix and AS level. Previous work suggested aggregating addresses into BGP prefixes [78]. We apply /24 prefix, BGP prefix and AS level aggregation to the master blacklist, produced by BLAG for the Mailxam dataset. We show their recall and specificity in Figure 11(a). Competing approaches sacrifice too much specificity to improve recall. While BLAG's specificity is always above 86%, specificity of BGP-prefix aggregation is 29% and specificity of AS-level aggregation is 35%. Thus BLAG again strikes the best balance between preserving specificity and improving recall.

B. Contribution of Individual Blacklists by Size

We ran BLAG on n largest blacklists, and varied n from 1 to 184 . We report the specificity and recall of these tests on Mailxam dataset in Figure 11(b). We observe that the recall increases as we add more blacklists but it has diminishing returns. There is 15.9% gain in recall for the first 40 blacklists. After which, there is a sharp increase in recall for the next 40 blacklists, then recall increases more slowly for the next 40, and finally recall seems to taper off once we reach 120 blacklists. The top 10 largest blacklists have recall of 12%, top 40 have have a recall of 15.9%, top 80 have a recall of 46.3% and all blacklists have a recall of 61%. As we add more blacklists, specificity drops slightly from 99% with top 10 blacklist, to 92% when top 80 blacklists are used and finally to 88% when all blacklists are used. This illustrates that having a moderate number (several tens) of blacklists would likely suffice to reap benefits of running BLAG.

C. Parameter l for Historical Decay

Parameter l controls the length of an address's history of offense, which should be considered for the historical score. If l is too small, it causes the reputation scores to decay quickly, and causes only the most recent offenses to be included in BLAG's blacklist. If l is too large, it causes all of the historical data to be considered, and BLAG becomes the same as historical blacklist approach. Ideally, an appropriate l maximizes the difference between the reputation scores for legitimate and malicious addresses. To determine the ideal l value, we calculate for each /24, the histogram of reputation scores for legitimate and malicious addresses in our training dataset. We then choose l, which maximizes the difference between these histograms for most of the prefixes. In our datasets, $l = 29$ days maximized the difference for 91.61% of the networks. The same approach is taken by PRESTA [84] to include historical addresses. Under deployment, l can be periodically determined when known legitimate senders (L) are refreshed.

D. Parameter K for Matrix Factorization

A critical parameter in non-negative matrix factorization (NMF) used in BLAG is the parameter K, which is the number of latent features. An ideal K will have the minimum error between the matrix $R(MxN)$ and the cross product of P and Q (see Section IV-B). Brunet et al. [54] suggested in using the smallest K, after which the *cophenetic correlation coefficient* starts decreasing. We evaluate different values of K by considering the most dense /16 prefix, consisting of 56,102 addresses, which are present in over 67 blacklists. We vary K from 2 to 67 ($K \leq min(M, N)$) and find that cophenetic correlation coefficient starts decreasing after K is 3.

We ran gradient descent with $K = 3$ until the root mean squared error (RMSE) between the original matrix R and matrix R' (obtained after the cross product of P and Q) fell below 1% or the number of iterations exceeded 20,000. We observed that 98.7%, 99.37% and 95.9% of prefixes in Mailxam, Miraixa and Darkexa datasets have RMSE less than 1%.

E. Parameter α for Choosing Addresses

Parameter α controls the set of addresses, which should be considered for the expansion phase in BLAG. Figure 10 shows that for each dataset parameter α trades in accuracy of BLAG with higher coverage. We see that as value of α increases, BLAG's specificity increases but recall drops. We set α to 8 for all the three datasets. We observe that there is a 5.9–14% gain in specificity and 9.9–35.1% reduction in recall when α changes from 0 to 8 for all the three datasets. Higher values of α (9–10), bring less improvement in specificity with much higher loss in recall. We observe that specificity increases only by 1.9–3.4%, while recall reduces by 10.1–12.3% for all the three datasets.

F. Parameter N_m for Mismanaged Prefixes

N_m determines how many addresses must be blacklisted from the same /24 prefix, to label this prefix as "mismanaged". We investigated different values of $N_m = (1, 255)$ on the Mailxam dataset (other datasets show the similar trend). Figure 11(c) shows the recall and specificity as N_m varies. As N_m increases, the specificity increases and recall decreases. With $N_m = 2$, the specificity improves by 31.83% and recall reduces by 1.3% when compared to $N_m = 0$ (i.e., when there is no classification of mismanaged prefix). For values of N_m greater than 2, there is only a small gain in recall, with much higher loss in specificity. For $N_m = 256$, the specificity improves only by 2% when compared to $N_m = 2$, but recall reduces by 51.1%.

G. Parameter β for Selective Expansion

β controls the number of addresses which will be selectively expanded if the address belongs to a dynamic or mismanaged network. Smaller the β, the more number of addresses will be included in the aggregated master blacklist. Figure 12 shows the improvement in specificities in three blacklists. We set $\beta = 1$ as it increases specificity by 8.8%, 14.1% and 12.7% for Mailxam, Miraixa and Darkexa datasets when compared to $\beta = 0$ which involves expansion of all the addresses belonging to dynamic or mismanaged networks. We observe that recall reduces at

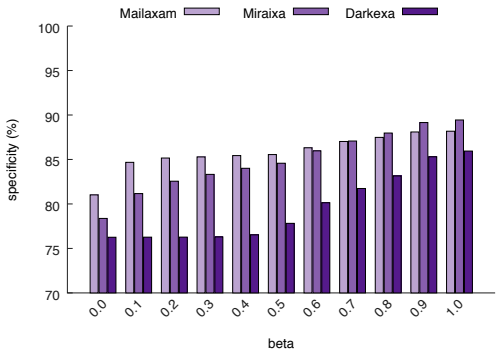


Figure 12: Change in specificities with parameter β.

the most by 2% in all three datasets because selective expansion is aimed to avoid /24 prefixes where blacklists have misclassifications.

VII. Related Work

In this Section we survey work related to blacklist analysis, creation or aggregation.

Analysis of Blacklists. Kührer et al. evaluated the effectiveness of fifteen publicly available malware blacklists by measuring accuracy and completeness on datasets consisting of parked domains, sinkholed addresses and active malware domains [63]. Pitsillidis et al. evaluated ten different blacklists on purity, coverage, proportionality and timing [71]. Purity was measured by comparing feeds to Alexa top websites and Open directory listing, whereas coverage, proportionality and timing were obtained by comparing feeds to one another. Both Kührer et al. and Pitsillidis et al. works support our own findings that blacklists are not accurate. Zhang et al. evaluated nine blacklists using traffic logs from a regional ISP [87]. They analyzed overlapping addresses between traffic logs and blacklists. But they were unable to measure the accuracy of blacklists, as the traffic in the logs was not labeled as malicious or legitimate. The main difference between these related works and ours is twofold. First, our main focus is on distilling accurate information from blacklists and aggregating it into a master blacklist; we use data about current blacklists performance merely to motivate our work. Second, we use an order of magnitude more blacklists than previous works.

Improving Blacklisting. Highly Predictive Blacklisting [86] (HPB) proposes a technique to create blacklists customized to the given network. The algorithm is based on an algorithm similar to Google's page ranking scheme, which identifies attackers that may target the specific customer, based on the attacks reported by other similar customers. Though this produces effective blacklists for a given network, HPB will not uncover new attackers, which have not targeted a specific customer group, while BLAG does not have this limitation. Soldo et al. [79] built on HPB. They extended it to use historical data about attack sources and destinations, and to use a recommendation system to predict possible attackers given a victim. In contrast, BLAG does not produce a victim-specific blacklist, but a generic one. Our recommendation system does not learn affinity between attackers and victims, but between attackers and blacklists, and we use it to improve recall, while keeping the specificity high. We expect that BLAG's blacklists may be able to filter more attacks than Soldo et al. approach.

There are several works which focus on improving spam mitigation using new blacklisting techniques. PRESTA [84] uses historical data from three spam blacklists provided by Spamhaus [44], to infer temporal and spatial properties of addresses and expand addresses into spatial regions, similar to our /24 prefixes. PRESTA does not consider the possibility of false positives from the expansion, which leads to lower specificity compared to BLAG, as seen in Section V. Sinha et al. [78] present how to improve spam blacklisting, by using a thresholding technique, which includes the number of sent messages into spammer identification process. They also present an expansion technique, which blacklists the entire BGP prefix if that prefix sent only spam. Though this technique is effective in detecting new spammers, expansion to BGP prefixes is too coarse-grained and can lower specificity, as shown in Section VI.

We could not directly compare Soldo et al. and Sinha et al. approaches to BLAG, because both these approach need data on attackers and victims, which is not publicly available.

VIII. Discussion

In this section we discuss possible attacks on BLAG, and some deployment issues.

Pollution. BLAG has no way, other than the reputation system, to differentiate between low-quality and high-quality information. Thus, if an attacker could produce a blacklist that is very similar to some reputable blacklist (e.g., by copying it) and if he included a few public servers in it, BLAG could conceivably propagate this information into its master blacklist. This could then lead to legitimate traffic from these public servers being dropped. Current blacklists could also be polluted by the same approach. BLAG makes polluted information less likely to propagate, than the use of individual blacklists. The attacker would have to carefully craft the polluted blacklist so that the servers reside in the same /16 as many malicious hosts; otherwise BLAG would be able to identify and discard low-quality information. Similarly, the attacker would have to insert just one or a few servers into these /16 ranges, or else their safety score would be too low for inclusion in the master blacklist. This means that the attacker cannot manipulate BLAG's master blacklist at will, but can just target those legitimate clients who share a /16 range with many recently malicious hosts. While limited, this effect is still very undesirable and we would like to prevent it.

BLAG can monitor the quality of each blacklist, e.g., how many misclassifications each blacklist usually makes on the second known-legitimate dataset $L\prime$. If a sudden increase is detected, BLAG can use machine unlearning [55] to selectively remove this list's historical data from the final

blacklist. Since BLAG processes data for individual /16 networks, only the reputation scores for the affected /16 networks would need to be recomputed. We leave the exact handling of pollution attempts for our future work.

Frequency of running BLAG. Initially, BLAG would start with some set of blacklists and it would be ran over their current and historical data. Once the reputation scores are computed, BLAG needs to be run only when a blacklist is updated. When addresses are added or removed in a snapshot, only the reputation scores for the encompassing prefixes must be recalculated.

Overhead of running BLAG. Blacklists could be updated very often, which may lead to large overhead to generate master blacklist. In our evaluation, there were about 4,000 updates per day and they took around 3 hours to process on a 4-core, 16GB RAM server. Since, BLAG evaluates blacklists at a level of /16 prefix, BLAG operation can be distributed among several machines to achieve scalability.

How can BLAG be used. Current blacklists are used to pre-filter known offender traffic, i.e., they are used proactively. BLAG's master blacklist can be used in the same manner. But because BLAG's specificity is lower than that of individual blacklists, one could also decide to use it reactively, to prioritize which traffic should be dropped. For example, when there is a heavy DDoS attack, when a worm is spreading, or when a new vulnerability becomes known. BLAG can also be used with ensemble filtering systems such as SpamAssassin [66] where multiple detection techniques are used in parallel on an email to decide if it is a spam or ham. In such cases, BLAG can become one of the detection techniques.

IX. Conclusion

Blacklists are widely used by network operators, but they usually miss many attacks. We have proposed BLAG– the system that can identify high-quality pieces of information from multiple blacklists, and aggregate them into a master blacklist, with some addresses expanded into /24 prefixes. Overall, BLAG has a higher recall than any single blacklist or their naive aggregation with minimal loss in specificity. BLAG also outperforms PRESTA, a competing approach, by having much higher specificity. We thus believe that BLAG could significantly improve network security, and lower collateral damage to legitimate traffic from blacklisting.

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