Exploiting Statistical and Structural Features for the Detection of Domain Generation Algorithms

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Abstract

Nowadays, malware campaigns have reached a high level of sophistication, thanks to the use of cryptography and covert communication channels over traditional protocols and services. In this regard, a typical approach to evade botnet identification and takedown mechanisms is the use of domain fluxing through the use of Domain Generation Algorithms (DGAs). These algorithms produce an overwhelming amount of domain names that the infected device tries to communicate with to find the Command and Control server, yet only a small fragment of them is actually registered. Due to the high number of domain names, the blacklisting approach is rendered useless. Therefore, the botmaster may pivot the control dynamically and hinder botnet detection mechanisms. To counter this problem, many security mechanisms result in solutions that try to identify domains from a DGA based on the randomness of their name.

In this work, we explore hard to detect families of DGAs, as they are constructed to bypass these mechanisms. More precisely, they are based on the use of dictionaries so the domains seem to be user-generated. Therefore, the corresponding generated domains pass many filters that look for, e.g. high entropy strings. To address this challenge, we propose an accurate and efficient probabilistic approach to detect them. We test and validate the proposed solution through extensive experiments with a sound dataset containing all the wordlist-based DGA families that exhibit this behaviour and compare it with other state-of-the-art methods, practically showing the efficacy and prevalence of our proposal.

Keywords: Malware, Botnets, Domain Generation Algorithm, DNS

1 Introduction

The ceaseless efforts of malware authors to enhance cybercrime with sophisticated techniques is creating a new “business” paradigm. Such a business has a myriad of monetisation sources including, but not limited to, ad injection, spamming, denial of service, ransomware-based extorsion or phishing. In this regard, one of the most critical aspects of such malware campaigns is the control and management of the compromised hosts. This enables the malware author, apart from compromising the victim’s security and privacy, to orchestrate further attacks and prolong the discovery of the attack.

In the past, the prevalent methodology was to establish a direct communication channel between the Command and Control (C&C) server and the infected devices. However, this strategy had several flaws, since blacklisting a specific IP or a domain name served as an effective takedown mechanism. Nowadays, to counter direct communication issues, cybercriminals try to use communication channels that disguise the traffic as benign and cannot be easily blocked, e.g. social networks or use multiple domains to manage infected hosts. In the latter case, the adversary uses a Domain Generation Algorithm (DGA) to periodically generate multiple domains which can be used as rendezvous points to retrieve updates and commands. However, only a few of them are registered. Therefore, the C&C server can be transferred from one domain to another without losing control of the compromised devices. In addition to the dynamic domain transfers, the lack of proper reporting from
domain registrars aggravates the problem, since requests made from law enforcement authorities and security practitioners may receive delayed responses, hindering botnet detection. Therefore, the use of a DGA introduces an asymmetry of cost for the attacker and the defender, as the former has only a minimal cost to register the domains while it is impossible for the latter to block all possible domains.

1.1 Motivation and Contributions

DGAs come in different flavours depending on how they generate the domain names. The general rule is that they use a pseudo-random generator to create a string that is used as the domain name that the infected hosts would query to reach the C&C server. To allow the botmaster and bots to generate the same list of domain names, the DGA contains a set of preshared secrets, e.g., the seed. If the generated domain name is a string that is completely random, then its entropy would be rather high. This creates a criterion allowing one to differentiate algorithmically generated domain (AGD) names from regular DNS queries.

To counter this detection method, some DGAs resort to using random combinations of words which are extracted from predefined dictionaries. Therefore, these DGAs are often referred to as wordlist-based DGAs. This way, wordlist-based DGAs bypass many security mechanisms as the generated domains not only have a low entropy, but they also appear to be generated and requested by humans. This is of particular relevance since more than 2/3 of the top domain list contains at least one English word, and around 1/3 are entirely composed by English words [57]. Therefore, distinguishing between benign and malicious word-based AGDs becomes a more challenging task.

In this work, we illustrate that AGDs can be easily identified by the fact that wordlist-based DGAs use a limited dictionary which results in often word repetitions. In this regard, we either exploit the well-known "birthday problem" and populate custom dictionaries from the Non-existent Internet Domains (NXDomains) that a host queries, or the structure of the domains they produce. Once the queries exceed some quota, we consider that a malware that uses a DGA has infected the host. Despite its simplicity, our method manages to be efficient in terms of both computational effort and detection, allowing it to be easily deployed in existing environments. Notably, the method is more efficient and accurate than current state of the art, managing to throttle all such DGAs after only a few NXDomain requests without the need for training. Moreover, beyond implementing an additional support layer to detect well-known DGA families, our method can detect new such DGA families, since it does not depend on training data nor is constrained by domain-specific features. Notably, our methodology is applied to a statistically sound dataset, containing all the known wordlist-based DGA families up to date and 3,027,300 domains, which is by far the largest and most complete dataset in the literature of studies for wordlist-based DGAs.

1.2 Organisation of this work

The rest of this work is structured as follows. In Section 2, we present the related work regarding DGAs and detection methods. Then, in Section 3, we discuss the proposed methodology for identifying the operation of a wordlist-based DGA malware, using only network traffic logs. In Section 4, we describe our experimental setup, the datasets we utilise and our results. Afterwards, in Section 5, we discuss the findings of our extensive experiments using our proposed methodology and compare it to the current state of the art. Finally, the article concludes discussing future work and summarising our contributions.

2 Related Work

Nowadays, malware developers use DGAs, which create a set of AGDs to communicate with C&C servers, overcoming the drawbacks of static IP addresses [5, 35]. In essence, DGAs use a deterministic pseudo-random generator (PRNG) to create a set of domain names [46, 38]. Therefore, the infected devices query a set of domains generated by the DGA till they resolve to a valid IP (i.e. the C&C
server), whose location may also change dynamically. In this regard, blacklisting domains is rendered useless as it implies many practical issues.

According to the literature, there are two main families of DGAs: (i) Random-based DGA methods, which use a PRNG to generate a set of characters to create a domain name, and (ii) Dictionary/Wordlist-based DGA methods, which use a predefined dictionary of existing words to generate such domains and thus, their detection becomes a more challenging task. There also exists a minor subset of DGA families that use valid domains that were previously hacked to hide their C&C servers (i.e. domain shadowing) [30] and DGAs that generate domain names that are very similar to existing valid domains or the ones generated by other DGA families [4] hindering the detection task. Considering the dependency of the pre-shared secret to time, Plohmann et al. [42] further categorise DGAs to time-independent and deterministic, time-dependent and deterministic, and time-dependent and non-deterministic. Fu et al. [21] proposed two DGAs which use hidden Markov models (HMMs) and probabilistic context-free grammars (PCFGs) and tested them on state-of-the-art detection systems. After analysing the outcomes by using metrics such as Kullback-Leibler (KL) distance, Edit distance (ED), and Jaccard index, their results showed that these DGAs hindered the detection rate of such approaches.

In the case of random-based DGA detection, a common practice is to analyse some features of the domain names and their lexical characteristics to determine whether a DGA has generated them [7, 54]. Moreover, auxiliary information such as WHOIS and DNS traffic (e.g. frequent NXDomain responses) is often used to detect abnormal behaviours [61, 24, 4]. Other approaches use machine learning-based techniques and combine the previous information to identify Random-based DGA such as in [24, 55, 31, 59].

Nevertheless, many researchers have recently started focusing on the detection of wordlist-based DGAs. In [14], authors propose the smashword score, a metric that uses n-gram overlapping combined with information provided from WHOIS lookups to detect AGDs. The WordGraph method [39] extracts dictionary information that is embedded in the malware using a graph-based approach, which models repetitions and combinations of domain name strings. In [29], authors use a machine learning approach based on recurrent neural networks trained using “familiar” (i.e. already known) dictionaries to detect wordlist-based AGDs. Similarly, the work presented in [45] focuses on AGD classification and characterisation, generating knowledge about the evolving behaviour of botnets. The authors of [3] propose a generative adversarial network (GAN), which can learn and bypass classical deep learning detectors. Thereafter, such acquired information is used as feedback to the system to improve the accuracy of the AGD detectors. Neural Networks are also used to classify domain names based on word-level information in [29]. More concretely, researchers use ELMo [40], a context-sensitive word embedding, and a classification network that consists of a fully-connected layer with 128 rectified linear units and a logistic regression output layer. In [50], the authors propose an improvement of Phoenix botnet detection [45] by using a modified Mahalanobis distance metric to perform classification as well as a variant of k-means to increase clustering effectiveness. The work described in [51] proposes a short-term memory network (LSTM), which uses raw domain names as features to perform binary classification. Yang et al. proposed a classification based on a set of features such as word correlations, frequency, and part-of-speech tags in [56]. Later, they enhanced their detection mechanism by the use of inter-word and inter-domain correlations using semantic analysis [57]. Spooren et al. [47] recently showed that their deep learning recurrent neural network is significantly better than classical machine learning approaches. More interestingly though, they showed that one of the dangers of manual feature engineering is that an adversary may adapt her strategy if she knows which features are used in the detection. To this end, they introduce properly crafted DGAs that bypass these classifiers. Berman [8] developed a method based on Capsule Networks (CapsNet) to detect AGDs. They compare their method with well-known approaches such as RNNs and CNNs, and the outcomes showed that the accuracy obtained by CapsNet was similar with better performance. Xu et al. [53] proposed the combination of n-gram and a deep CNNs to create an n-gram combined character-based domain classification (n-CBDC) model. Their model runs in an end-to-end way and does not require from domain feature extraction, enhancing its performance. Vinayakumar et al. [52] implemented a set of deep learning architectures with Keras Embedding and classical machine learning algorithms to classify DGA families. Their best reported
configuration is obtained when using RNNs with SVM with radial basis function (SVM-RBF). For a detailed overview and classification of methods of how malicious domains can be detected, the interested reader may refer to [60].

In a recent work [36], the authors extend the notion of DGAs into a more generic one, namely Resource Identifier Generation Algorithms (RIGA) which allows the use of other protocols beyond DNS. In this regard, authors show how decentralised permanent storage (DPS), although being a useful technology able to enhance a myriad of applications, has some potential drawbacks and exploitable characteristics for armouring a botnet as already exploited in the real world [27], primarily due to its immutability properties. Therefore, the authors showcase the potential risks and opportunities for malware creators and raise awareness about the symbiotic relationship between DPS and malware campaigns. Finally, due to recent advances and the widespread use of covert/encrypted communication channels (e.g. DNSCurve, DNS over HTTPS and DNS over TLS) malware creators have an additional layer to hide their communications, rendering traditional DGA detection mechanisms useless. Nevertheless, as shown in [37], NXDomain detection can still be performed in such a scenario as well as feature extraction so that DGA families can be further classified with high accuracy.

In addition to the related work analysis, we argue that it is also worth discussing the fact that NXDomain requests may be a result of user typewriting errors. Each human produces different typing patterns depending on the writing surface (e.g. keyboard, smartphone, or larger touch screen surfaces such as tablets) [20] and according to its physical and physiological conditions [19, 13], which can be used, for instance, to uniquely identify an individual. Nevertheless, typewriting errors are strongly influenced by the language and therefore, exhibit common characteristics regardless of one’s typing pattern. The most common typing errors [15, 41] (more than 80%) are caused by (i) transposition of two adjacent letters, (ii) adding one extra letter, (iii) one missing letter or (iv) one wrong letter. Therefore, such errors can be corrected backspacing or moving the cursor to the point at which the error occurred and then retyping [25].

As previously discussed, although typewriting errors may lead to NXDomain with high probability, usually lots of similar domain names to the original are often registered [10, 18] to avoid homograph attacks [22]. Moreover, several techniques which aim to overcome homograph attacks can be found in the literature. For example, in [49], authors designed an accurate typo categorisation framework and found that typosquatting using parked ads and similar monetisation techniques exist for popular domains as well as in the Alexa list. To mitigate this problem, the authors implemented typosquatting blacklists and a browser plugin to prevent mistyping at the user side. In the case of [34], the authors analyse the main typosquatting issues and monetisation market behind it and recall the effectiveness of several policies and efforts to regulate typosquatting. More recently, novel approaches [48] developed by the Google Chrome security team, implement suggestions for lookalike URLs, which also prevent typewriting errors. These techniques, added to the fact that most domains are queried after using a search engine, historical data and bookmarks, vastly reduce the number of domains accessed directly through typewriting [9, 6].

Therefore, we can safely assume that typosquatted domains or homograph attacks represent a marginal percentage or potential danger (compared to DGA queries, which are much more frequent) taking into account the aforementioned prevention and security measures.

3 Proposed methodology

As already discussed, wordlist-based DGAs have predefined dictionaries that they use to create the possible domains that the malware would try to connect to find the C&C server. In our methodology, we exploit the fact that this set is often rather constrained, so we expect to have often repetitions of words in the NXDomain requests. The general methodology can be summarised as follows. A monitoring mechanism collects all the NXDomain requests performed by hosts. These domains are split into words, and those words are divided into buckets. The buckets are filled with words either statistically (each word has an individual bucket) or because they fit a specific pattern. Once a bucket, or a set of buckets, reaches a threshold, an alert is raised.
In what follows, we assume that the monitoring mechanism has a cache that stores the result and would either periodically wipe them after an epoch $T$ or wipe records that are older than $T$. This prevents the mechanism of reporting attacks as a result of, e.g., old typing errors which are stacked over time.

To facilitate the reader, we consider a simple scenario and gradually build on this one to describe our proposal. In our scenario, we have a wordlist-based DGA which selects two words from a dictionary of $n$ words. It adds a separator symbol (e.g., -) between them, and then appends a top-level domain (TLD) from a predefined set. If we assume that $n$ is small, then from the well-known “birthday problem” [33] we expect to have a collision, that is a word being repeated, in approximately $\sqrt{n}$ domain name generations. More precisely, the latter is expected to happen with 50% probability.

Setting the threshold of repetitions too low, e.g., 2, it is evident that may lead to many false positives as a user may have mistyped a domain name. This small amount of false positives is an acceptable trade-off in the event of human errors; as described in Section 2). Although typewriting attacks are much less frequent than DGA-based malware, as discussed in Section 2, one may set the threshold for repetitions of words in domain names higher to allow for some grace for typos. In what follows, we denote this threshold as $t$.

Generalising the above, one DGA may have $k$ dictionaries and generate each fragment of the domain name by randomly selecting one word from each dictionary. Therefore, we may formalise our problem as follows:

**Problem setting:** Let us assume that a DGA has $k$ dictionaries $d_i$, $i \in \{1, \ldots, k\}$. The DGA uses words (denoted as $w$) to create domain names of the form $\text{dom}$ such that:

$$\text{dom} = w_1|w_2|\ldots|w_k, \ w_i \in d_i, \ \forall i \in \{1, 2, 3, \ldots, k\}.$$ 

That is, $\text{dom}$ is the ordered concatenation ($|$) of $k$ words by randomly selecting one word from each dictionary and putting them in the same order as their dictionaries. Find the probability $p$ of having at least one word from any of the dictionaries being selected at least $t$ times, for $t$ constant.

It is clear that the case of having one dictionary ($k = 1$) and requesting one collision ($t = 2$) is the well-known birthday problem. Levin [28] and Diaconis and Mosteller [16] have thoroughly studied the birthday problem and its extensions. Based on their proofs, we have that the probability $p$ of having $t$ collisions on a dictionary of $L$ words in $n$ trials is subject to the following approximation:

$$\frac{ne^{-n/Lt}}{(1 - \frac{n}{L(t+1)})^{1/t}} \approx \left( L^{1-t} t! \log \left( \frac{1}{1 - p} \right) \right)^{1/t}.$$

Therefore, solving for $p$ we have that:

$$p \approx 1 - \exp \left( - \frac{L^{1-t} \left( ne^{-\frac{n}{L}} \left( 1 - \frac{n}{L(t+1)} \right)^{-1/t} \right)^t}{t!} \right).$$

From the latter approximation, and the fact that in the generic wordlist-based DGAs, discussed above, the collisions may affect different dictionaries are independent; one can compute the probability of a $t$-collision as follows:

$$P(t - \text{collision}) = \sum_{i=1}^{k} p_i,$$

where:

$$p_i = 1 - \exp \left( - \frac{L_i^{1-t} \left( ne^{-\frac{n}{L}} \left( 1 - \frac{n}{L_i(t+1)} \right)^{-1/t} \right)^t}{t!} \right).$$
and $L_i$ denotes the length of dictionary $d_i$.

Going a step further, let us assume that we have captured an NXDomain name request from a host. We may split the pattern to see the name in terms of structure. For instance, the domain name consists of 2 or 3 words with a total length above $M$ characters. Note that DGAs tend to have rather long domain names to, e.g. maximise the chances of purchasing the domains they want and avoid compromised machines contacting existing domains. Therefore, due to the way wordlist-based DGAs work, requests to NXDomains which have long names or with a specific amount of concatenated words may imply the existence of an infected machine. More precisely, wordlist-based DGAs often have a static template of the form, e.g. $w_1||w_2$.TLD (see DGAs like nymaim, pizd, and suppobox) or $w_1||w_2$$...$$|w_m$.TLD so that:

$$|w_1| + |w_2| + ... + |w_m| > M,$$

which contents would change according to each DGA. As it is shown in Section 4, typical user DNS queries do not follow this template.

Therefore, the proposed methodology is a two-layer filter for the collected NXDomains. By default, DNS queries are performed in cleartext format and can be captured by any network device that is hosted in the same network. Therefore, a network monitoring device can passively collect all DNS queries performed in the network and submit the NXDomains for processing in our two-filter mechanism. The first filter has a threshold based on word repetitions, while the second one keeps track of the patterns that recent domains have in terms of words, letters and structure. The proposed methodology is illustrated in Figure 1.

First, the network monitoring mechanism collects all the DNS queries and logs all NXDomain requests. Each such request is analysed by the two filters to check whether a threshold is exceeded. To do so, we first remove the TLD of the domain request, and we keep only the SLD which is analysed. The bulk of the literature studies SLDs only, as TLDs offer little information and they are well-known and fixed. Third level domains, since any anomaly in them, can be easily detected and handled controlled by the owner of the SLD are not considered in the related work. Next, the first filter receives as an input the SLD, splits it into words and sets a counter for each word that appears in such analysis. Once the counter of a word exceeds a given threshold $T$, a warning is issued. In parallel, the SLD is analysed for structural patterns, e.g. number of words, total length etc. as discussed in section 4. Again, if the counter that keeps track of repetitions of these patterns exceeds a given threshold $T'$, a warning is raised.

As it will be discussed in Section 5, the two-layer approach manages to provide high reliability, accuracy, and robustness. Moreover, due to the template that such AGDs are expected to have, our methodology is generic enough to counter other and non-reported wordlist-based DGAs.

### 4 Experiments

In this section, first, we describe the setup and methodology of our experiments. Next, we use the implementation of several DGAs, as provided by researchers who have reversed engineered the corresponding malware that embeds them, the real-world captures of the DGArchive, and two DGAs that were designed to bypass machine learning algorithms. More concretely, we study the following DGA families: beebone, banjori, gozi, matsnu, nymaim2, pizd, rovnix, suppobox and volatilecedar. Apart from studying only wordlist-based DGAs, we include in our dataset two arithmetic-based DGAs (beebone) and banjori and one permutation-based (volatilecedar) to see the effectiveness of our method in other families of DGAs. Finally, we have included the two DGA families from that we refer to as decept1 and decept2 which were crafted to bypass machine learning-based mechanisms. Table 1 provides an overview of our dataset. To this end, the table shows how many samples each DGA has and how many seeds. Moreover, we provide ten AGDs from each DGA in our dataset to facilitate the reader in understanding the AGDs of each DGA produces. The underlying dictionaries vary in length.

1. https://github.com/baderj/domain_generation_algorithms
2. https://github.com/andrewaeva/DGA
3. https://github.com/ynvb/ExplosiveScripts
origin, and amount for each DGA. More precisely, matsnu contains two dictionaries, one for verbs (878) and one for nouns (1008). Depending on the seed its AGDs will either always start from a verb or a noun. Then, using the seed for its PRNG, matsnu selects one word from each dictionary iteratively from each dictionary, until the length of the domain exceeds 24 characters. nyaim2 uses two dictionaries, one for the first word (2450 words) and one for the second one (4387 words) which are concatenated either directly without any separator or with the “-” character. pizd uses by default a wordlist containing 384 words and uses a PRNG to select two words and concatenate them to generate an AGD. rovnix uses as its source the US Declaration of Independence. The dictionary contains all the alphanumeric words of the document. To construct an AGD, rovnix selects words according to a PRNG until the selected words exceed the 20 characters. gozi is a variant of rovnix. Its various dictionaries originate from various public domain documents that are unlikely to be moved to another location, e.g. Request for Comments pages and the GNU Lesser General Public License. From these documents, gozi splits the documents according to stop characters (spaces, commas, etc.) and selects the words with at least three characters that contain only letters. From this wordlist, the PRNG selects random words that are concatenated so that the resulting AGD contains between 12 and 23 characters. Suppobox in the three seeds that have been identified so far has a dictionary of 384 words from which it selects two random words and concatenates them.

In our dataset, we have also added the top 1 million websites from Alexa. The reason for including this is to have some ground truth of benign traffic and illustrate the domains that an actual user would use is significantly different from the ones that would be derived from a DGA, even if they are made to do so. It should be noted here that the Alexa top 1 million dataset contains web pages and not domains. Therefore, there are repetitions of domains, e.g. blogspot. Moreover, there are several Internationalized domain names (IDN) (i.e. domains that start with the characters xn-- therefore, the domain name cannot contain any word. We opted to remove the latter domains and to keep each domain once. Note that up to now, there is no DGAs using IDN domain names. Therefore, the alexa dataset consists of 793,606 domains.

Using real data from the DGArchive and the reversed code, we collect the set of the domain names they create. The total AGDs are 2,533,694 and adding the benign domains from alexa; we end up with a dataset of 3,327,300 domains. Therefore, each domain in these datasets is processed to extract the words that were concatenated to generate them. This is achieved with the use of

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3https://www.icann.org/resources/pages/idn-2012-02-25-en
Table 1: Overview of our dataset.

| DGA    | Type       | # of samples | Seeds | Sample domains                                                  |
|--------|------------|--------------|-------|----------------------------------------------------------------|
| alexa  | Benign     | 793,606      | -     | google.com, youtube.com, tmall.com, baidu.com, qq.com          |
| beebone| Arithmetic | 210          | 2     | backdates0.com, backdates0.org, backdates0.net, backdates0.biz, backdates0.info |
| banjori| Arithmetic | 452,235      | 35    | andersensinaix.com, xjrrsensinaix.com, hhfrsensinaix.com, fnorsensinaix.com, fnorsensinaix.com, qcwrsensinaix.com |
| deceit | ML         | 150,000      | 1     | ytrbegofitr8h, rithlundiat, tarenoth200quymuroep, hatoranfa, xunrvrstbe |
| deceit2| ML         | 150,000      | 1     | taferstick, pblogalmarportran-f, martapord, joc-davingsbiosk, priations |
| gozi   | Wordlist   | 216,355      | 104   | penarumsalpaesthodie.com, quodqibusfulminatcur.com, defunctorumullamrelaxat.com, vi-niarumcuramhabet.com, nissacerdotipapefalse.com |
| matsnu | Wordlist   | 117,401      | 3     | starsendbottomhabitshake.com, causeirongrounndnet-tellstart.com, cultureexploredogdistrict.com, sizeprogrambillsaypointpot.com, tourmentionboneconcertadmire.com |
| nymaim2| Wordlist   | 23,424       | 1     | squirting-right.net, unitsedgar.net, sexuality-giant.net, utilitiespour.ki, vermontfeatures.ad |
| pizd   | Wordlist   | 10,000       | 1     | abovevshare.net, alreadyvshare.net, actionprobable.net, althoughprobable.net, actionseveral.net |
| rovnix | Wordlist   | 100,000      | 1     | theirtheandaloneinfo.com, thathistoryformtertrial.com, tothelayingthatarefor.com, definebritainhasforhe.com, tosecureonweestablishment.com |
| suppobox| Wordlist   | 1,313,571    | 3     | possibleshake.net, mountainshare.net, possible-share.net, perhapsnearly.net, windownearly.net |
| volatilecedar | Permutation | 498 | 2 | deotntexplorer.info, dotnetexplorer.info, dotnetexplorer.info, dotnetexplorer.info |
| **Total** |            | **3,327,300** |       | **Wordninja**[^1] a natural language processing (NLP) method that probabilistically splits concatenated words based on English Wikipedia uni-gram frequencies. |

[^1]: https://github.com/keredson/wordninja

In both filters, we assume that the network monitoring device intercepts all the NXDomain requests from each device and analyses them for each one individually. For the sake of clarity, we assume that the network monitoring device gets as input a stream of NXDomain requests from only one device. Moreover, we assume that the device is infected by only one malware with DGA capabilities, and therefore the malware uses one seed. In our experiments, this practically means that each one of them has to be executed per DGA family and using one seed at a time. We argue that this is strategy is correct as the malware will not manage to connect directly to the C&C server and several connections would be attempted before the malware manages to connect and receives the command to, e.g. use a different dictionary/seed. Note that in our DGA dataset, the different seed in several cases translates to the use of another dictionary.

In the first set of experiments, we test the frequency of word collisions on specific thresholds. More precisely, we split each domain name in words and record their occurrences if their length is more than three letters to avoid articles, pronouns etc. Based on a threshold of how many occurrences we expect from an AGD during an epoch, we monitor all NXDomain requests and raise an alert when the threshold is reached. To provide better insight on these results, more to than simply reporting the first time that an NXDomain query is performed for each AGD and seed in our dataset, we shuffled them and made the same measurement 1,000 times. In Figure[2] we illustrate the results for different threshold levels, which range from 3 to 7. By shuffling the domains that a DGA generates, we test the DGA with different possible seeds, far more than the ones we originally had. Since the use of different seed is a common practice in malware, we may study how our methodology performs in different settings, and show that it is generic enough to be used in various configurations. Although this threshold can be modified, we claim that three unrelated NXDomain queries that contain the...
same word are likely not to be generated by a human, according to Section 2 as well as discussed in our problem setting. This hypothesis is confirmed from our first experiment, which shows that our word filter is able to detect the domains generated by each family of DGA accurately.

Figure 2: Number of domains, generated by each DGA family, that are needed to reach the strike threshold.

Figure 3: Textual statistics for Alexa top 100K and the DGA families studied.
We conducted another set of experiments to study the statistical difference that the wordlist-based DGAs have from regular domains. Intuitively, we argue that the “poor” dictionary that these DGAs have would result in often repeating the same words in NXDomain queries as well as exhibiting some identifiable patterns. To this end, we analyse the textual statistical properties of the previously selected DGA families. Next, we compare them with those obtained in the case of Alexa top 1 million domains, and we depict the results in Figure 3. Based on these statistics, we create a filter as follows. We keep a short registry of the five most recent NXDomain requests, and we check whether any of the following criteria holds:

- All the requests are above ten characters.
- The amount of words in all requests are the same.
- The amount of words in all requests is above 2.
- The amount of the “short” words (less than four characters) are more than 2 in all requests.
- All the requests are made to the same SLD and different TLD.

The results of this process are illustrated in Figure 4. While this pattern approach introduces a bias in terms of language constraints, it is something that can be resolved by extending the dictionary of the underlying splitting algorithm. This extension may solve the issue for Latin-based dictionaries; however, this does not resolve the case of IDNs. Apparently, this filter manages to efficiently determine the lexicographical structure of the domain name, having high accuracy and low false positives and negatives. Moreover, it complements the previous filter by keeping a record of how many times a specific lexicographical structure was identified. Should these occurrences pass a threshold during a predefined epoch, the corresponding alert is raised.

As in the previous case, we performed our experiments 1,000 times. It is evident that our filter shows significant differences between AGDs and alexa. Notably, while there are some outliers for all DGAs the average of the counter is close to 5, with the highest being 5.24 from suppobox, while alexa had an average of 24.19 requests. We believe that the above illustrate that almost all DGAs could be identified with at most six requests.

Finally, we used our pattern approach on the hard to detect DGAs crafted in [47]. Both DGAs scored higher than the other DGA. Interestingly, the average of 1,000 experiments showed that decept was marginally harder than decept2, requiring 7.82 and 7.115 queries in average, respectively.
5 Discussion

In this section, we discuss the results of the experiments of the previous Section 4 as well as the main benefits of our approach and how it compares to the current state of the art. The results depicted in Figure 2 show that all the DGA families evaluated can be detected with only a few NXDomain queries (each domain resulting in a set of processed words), except nymaim2. This means that the AGDs generated by them tend to repeat words with statistical significance, as detected by our word-based filter. In the simplest case (i.e. with a threshold of 3 words, cf Figure 2a) we can detect AGDs with less than 30 NXDomain queries in almost all cases. For instance, the malware gozi uses 3 times the same word after generating 28 domains (see Figure 2a). In addition, the growth pace exhibited in Figure 2, in terms of NXDomain queries needed to reach from 3 to 7 strikes, exhibits the same growth pace as the probabilities defined in Section 3. The latter implies that, proportionally, the number of strikes grows faster than the number of NXDomains analysed.

In the case of nymaim2, the results show that we need a high amount of NXDomains to find coincidences (see Figure 2f). This occurs because nymaim2 uses a predefined structure to create domains in which two words, selected from two separate dictionaries with 2450 and 4387 words, respectively, are appended to a TLD (i.e. the number of possible TLDs is 74). Therefore, the amount of possible combinations hinders its detection. Nevertheless, this variability is only in the dictionary, and since the structure remains the same, it is captured by our pattern filter. It is worth noting that beebone needs a constant number of queries to be detected by our word filter as the words that act as prefix/suffix are constant (cf Table 1) in all queries. Therefore, they both trigger the alert in as many queries as the threshold is.

It is clear from Figure 3 that benign domain names most likely consist of at most three words containing less than ten letters in total. Therefore, NXDomain requests that do not meet these criteria can be considered as ‘suspicious’ by our pattern-based filter. Our claim is verified by the results of our pattern filter in alexa (cf. Figure 4), since the number of domains needed to pass the threshold is far higher than those required by the rest of DGAs. Note that the pattern-based filter can fully capture nymaim2 behaviour (as well as the rest of families, with few exceptions) so that we can raise an alert faster than our word-based filter in such cases.

Finally, it is worth noticing that the bulk of hash and arithmetic-based DGAs, such as Dyre, Gameover, Gspy and Omexo, produce domains that are long (more than 15 characters) and as they are hex-encoded, they hardly create words. Therefore, all such AGDs fail our structure criterion. Moreover, AGDs generated by other DGA families, including DNS Changer, DiamondFox, DirCrypt and EKforward also fail our structure criterion, as they might generate shorter domains, but the produced domains do not have meaningful words.

Table 2: Comparison of the detection accuracy (in percentage) between to most recent state-of-the-art methods. In each case, we report the best values.

| DGA      | [20] | [51] | [8] | [14] | [53] | [57] | [52] | [21] | Our Method |
|----------|------|------|-----|------|------|------|------|------|------------|
| beebone  | 90.46| 100  | 74.9|      |      |      |      | 100  |            |
| banjori  | 99.84| 100  | 80.8| 99.78| 0    |      |      | 100  |            |
| deception|      |      |     |      |      |      |      | 100  |            |
| deception|      |      |     |      | 100  |      |      |      |            |
| gozi     | 0    | 77.3 | 97.98|      |      |      |      | 100  |            |
| hmm-dga  |      |      |     |      | 48.67| 100  |      |      |            |
| matsnu   | 98.74| 0    | 0   | 89.1 | 96.91| 100  |      | 100  |            |
| nymaim2  |      |      |     |      |      |      |      | 100  |            |
| pcfg-dga |      |      |     |      | 48.1 |      |      | 100  |            |
| pizd     | 98.76|      |     |      | 91.96|      |      | 100  |            |
| rovnix   | 98.71|      |     |      | 80.5 |      |      | 100  |            |
| suppobox | 98.74| 35.42|     |      | 87.82| 56.8 |      | 98.18 | 84.17     |
| volatilecedar | 100 | 100  | 95.8|      |      |      |      | 82.1 | 100         |


To showcase the efficacy of our method, we compared it with the most recent state-of-the-art. The outcomes of each method are depicted in Table 2. It can be observed that none of the methods compared includes the whole list of word-based DGAs analysed in this article, as stated in the Motivation section. In terms of accuracy, we can observe that most of the methods succeed to provide a remarkable accuracy in at least one of the families, with the exception of the work presented in [32]. Moreover, in many cases, the size of the samples evaluated is extremely small (i.e. which evinces the difficulty to obtain a quality database such as the one used in this article). For instance, in the case of Tran et al. [51], we observe that authors train their system with a rather constrained dataset, e.g. they use 42,166 \textit{banjori} domains and only 42 \textit{beebone} domains. Another example can be found in [14], where authors use only 250 samples in the case of \textit{suppobox}. After a deeper analysis of the outcomes, we observed a common trend in most of them. More concretely, when a method can accurately detect a DGA family, it fails to detect others, due to the particular characteristics of each DGA, as seen in [21, 8, 14, 57, 52]. Note that there are cases where the method is not able to capture any instance of a DGA (i.e. the reported accuracy is 0). In addition, some of the families are only explored in this paper (i.e. \textit{nymaim2}, \textit{pcfg-dga}, and \textit{hmm-dga}), which are only analysed by their creators [21, 47] by using state-of-the-art methods. More precisely, in the case of \textit{hmm-dga} and \textit{pcfg-dga}, the accuracies reported are below 49% for both DGAs using the Botdigger [58] DGA detector, and in the case of \textit{decept} and \textit{decept2} the accuracy is below 85% using LTSM. Finally, it is worth mentioning that when some DGAs change their seed, the accuracy of their detection drops significantly, as stated by Berman [8] in the case of \textit{pizd} and \textit{suppobox}. However, the latter behaviour does not affect our method, since it only implies a restart of the word counter. In addition, we did not include the works presented in [29] and [39] due to their database size, since they train their methods with a high amount of domains, in some cases orders of magnitude higher than the queries needed by our method to detect them. For instance, in [39], authors use 8-day real traffic data, resulting in thousands of domains. In the case of [29], they use tens of thousands queries generated by \textit{banjori}, \textit{gozi}, \textit{nymaim2}, \textit{rovnix}, \textit{suppobox}, \textit{matsnu} (i.e. with low detection accuracy in the case of \textit{matsnu}, which is below 0.16), and hundreds of queries in the case of \textit{beebone} and \textit{volatilecedar}, to train their system using a 10-fold scheme. Another recent work, proposed by Yang et al. in [57], uses machine learning and semantic analysis to detect two DGA families, namely \textit{suppobox} and \textit{matsnu}. Using different dataset configurations, they report accuracies between 83.63% and 86.23% for \textit{suppobox} and between 88% and 100% in the case of \textit{matsnu}. Although they also consider an additional set of unclassified word-based AGDs, their average detection accuracy is 80.58%, which is significantly lower than our proposed work. Finally, in work presented by Spooren et al. [47], the authors achieve different accuracies depending on the classifier and the parameters. In general, the random forest classifier is rendered useless for \textit{decept} and \textit{decept2} with accuracies below 60%. In the case of LTSM, the classification accuracy for such families is also lower (i.e. 85.5%) than ours.

In summary, in addition to absolute accuracy in DGA detection, our method enables a set of benefits, compared to other well-known literature methods based on neural networks or other feature-based classification mechanisms [26, 51, 59, 29, 57, 47]. More concretely, our method can be deployed instantly and is parallel by design. In addition, it does not require training, contrary to the aforementioned approaches, enabling the adaptable discovery and detection of novel DGA families. Note that, since they require training, Neural Networks are sensitive to dictionary changes, hence providing less robust outcomes for real-time DGA analysis than our approach. As a further enhancement, our pattern-based setting can filter out almost instantly DGAs, which means that only a minimal subset needs to be further analysed. Moreover, our word-based filter only needs a small number of NXDomain queries to achieve DGA detection. This also enables personalised policies, where benign domains that fall out of the threshold can be whitelisted since their amount would be relatively small. We also argue that the fast detection of \textit{decept} and \textit{decept2} signify another advantage of our methodology. More precisely, while these DGAs are crafted to exploit many character features, they fail to be meaningful enough and end up being detected by our pattern filter. Finally, paired with recent advances in human typewriting error detection and application layers preventing such behaviour, the robustness of our method can be highly enhanced.

It is worth noting that the proposed method is directly affected by the language of the dictionaries
and their size. Large dictionaries, as seen in the case of nymain2, imply a longer detection threshold. On the other hand, the case of using other languages for the dictionaries implies another issue for the method. Nevertheless, the latter is the same for all methods targeting these DGAs, as they all depend on the knowledge of the used language to split the words accordingly and perform their analysis.

6 Conclusion

In this work, we analyse the current state of the art in Domain Generation Algorithms, a family of algorithms that use pseudo-random generators to create a set of AGDs, used as rendezvous points for their C&C servers. More concretely, we focus on DGA families which use wordlists to generate such domains. Therefore, to provide efficient and accurate detection of wordlist-based DGAs, we propose a probabilistic method inspired by the “birthday paradox” and the structure that these generators have. In this regard, our method exhibits a series of benefits compared with other state-of-the-art methods, since it can be instantly deployed, requires no training and can filter the bulk of domain names in terms of their pattern construction, enabling efficient and adaptable DGA detection. Moreover, extensive experiments using state-of-the-art benchmarks show that we need between 3 and 27 NXDomain queries (with strike threshold set to 3) to detect DGA malware with high confidence using our word-based filter. Future work will focus on analysing the statistical properties of benign domains (including IDN), especially in the case of Alexa, to enhance their classification using different wordlist-based probabilistic word splitters.

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