Polymorphic Blending Attacks

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Abstract

A very effective means to evade signature-based intrusion detection systems (IDS) is to employ polymorphic techniques to generate attack instances that do not share a fixed signature. Anomaly-based intrusion detection systems provide good defense because existing polymorphic techniques can make the attack instances look different from each other, but cannot make them look like normal. In this paper we introduce a new class of polymorphic attacks, called *polymorphic blending attacks*, that can effectively evade byte frequency-based network anomaly IDS by carefully matching the statistics of the mutated attack instances to the normal profiles. The proposed polymorphic blending attacks can be viewed as a subclass of the *mimicry* attacks. We take a systematic approach to the problem and formally describe the algorithms and steps required to carry out such attacks. We not only show that such attacks are feasible but also analyze the hardness of evasion under different circumstances. We present detailed techniques using `PAYL`, a byte frequency-based anomaly IDS, as a case study and demonstrate that these attacks are indeed feasible. We also provide some insight into possible countermeasures that can be used as defense.

1 Introduction

In the continuing arms race in computer and network security, a common trend is that attackers are employing polymorphic techniques. Toolkits such as ADMmutate [17], PHATBOT [10], and CLET [5] are available for novices to generate polymorphic attacks. The purpose of using polymorphism is to evade detection by an intrusion detection system (IDS). Every instance of a polymorphic attack *looks* different and yet carries out the same malicious activities. For example, the payload of each instance of a polymorphic worm can have different byte contents. It follows that signature-based (misuse) IDS may not *reliably* detect a polymorphic attack because it may not have a fixed or predictable signature, or because the invariant parts of the attack may not be sufficient to construct a signature that produces very few false positives. On the other hand, each instance of a polymorphic attack needs to contain exploit code that is typically not used in normal activities. Thus, each instance looks different from normal. Existing polymorphic techniques [28] focus on making the attack instances look different from each other, and not much on making them look like normal. This means that network payload anomaly detection systems can provide a good defense against the current generation of polymorphic attacks. However, if a polymorphic attack can blend in with (or look like) normal traffic, it can successfully evade an anomaly-based IDS that relies solely on payload statistics.

In this paper, we show that it is possible to evade network anomaly IDS based on payload statistics using a class of polymorphism that we call polymorphic blending. A polymorphic blending attack is a polymorphic attack that also has the ability to evade a payload statistics-based anomaly IDS. In addition to making all the mutated attack instances different, an attacker (or the attack code) attempts to make them appear normal by transforming each instance in such a way that its payload characteristics (e.g., the byte frequency distribution) fit the normal profile used by the anomaly IDS. Since polymorphic blending attacks try to evade the IDS by making the attacks look like normal, they can be viewed as a subclass of the *mimicry* attacks [29, 33].

This paper makes several contributions. We study the class of polymorphic blending attacks against byte frequency-based network anomaly IDS, which was introduced by Kolesnikov et al. in [12]. We present the general techniques and design considerations for such attacks. We provide rationales of why these attacks are practical and show that network anomaly IDS based on payload statistics do not guarantee adequate protection against sophisticated attacks.

Using 1-gram and 2-gram PAYL [35, 36] as a case

study, we take a systematic approach to the problem and describe the necessary steps required to carry out an effective attack. Our work provides insight into not only how such an attack can be performed, but also how hard it is to launch these attacks under different circumstances. We analyze the amount of learning required for the attacker and the time and space complexity required for blending. We use a real attack vector [8] to implement a polymorphic blending attack and provide experimental evidence that our attack can effectively evade detection. We also discuss possible countermeasures that a defender (e.g., IDS designer or operator) can take to decrease the likelihood that a polymorphic blending attack will succeed.

Organization of the paper The rest of the paper is organized as follows. We discuss related work in polymorphic attacks and detection in Section 2. In Section 3, we introduce polymorphic blending attacks and discuss the general techniques and design issues of polymorphic blending attacks. We present our case study in Section 4 and conclude the paper in Section 5.

2 Related Work

Transforming attack packets to avoid detection is a common practice among attackers. Attackers can exploit the ambiguities present in the traffic stream to transform an attack instance to another so that an IDS is not able to recognize the attack pattern. IP and TCP transformations ([11, 22]) techniques are used to evade NIDS that analyzes TCP/IP headers. Vigna et al. [31] discussed multiple network, application and exploit layer (shellcode polymorphism) mutation mechanisms. A formal model to combine multiple transformations was presented by Rubin et al. [24]. Multiple tools such as Fragroute [26], Whisker [23], and AGENT [24] are available that can perform attack mutation.

Code polymorphism has been used extensively by virus writers to write polymorphic viruses. Mistfall, tPE, EXPO, and DINA [28, 37] are some of the polymorphic engines used by virus writers. Worm writers have also started using polymorphic engines. ADMmutate [17], PHATBOT [10], and JempiScodes [25] are some of the polymorphic shellcode generators commonly used to write polymorphic worms. Garbage and NOP insertions, register shuffling, equivalent code substitution, and encryption/decryption are some of the common techniques used to write polymorphic shellcodes.

Quite a few approaches have been proposed to detect polymorphic attacks. In [30], Toth et al. proposed a technique to locate the presence of executable shellcode inside the payload. They used abstract execution of network flows to find the *MEL* (Maximum Executable Length) of the payload. The flow is marked suspicious if its *MEL* is above certain length. Chinchani et al. [2] performed fast static analysis to check if a network flow contains exploit code. STRIDE [1] focuses on detecting polymorphic sleds used by buffer overflow attacks. In [14], Kruegel et al. used structural analysis of binary code to find similarities between different worm instances. Using a graph coloring technique on a worm's control flow graph, this approach is able to accurately model the structure of the worm. Given a set of suspicious flows, Polygraph [20] generates a set of disjoint invariant substrings that are present in multiple suspicious flows. These substrings can then be used as a signature to detect worm instances. In a recent work, Perdisci et al. [21] proposed an attack on Polygraph [20] where noise is injected into the dataset of suspicious flows so that Polygraph is not able to generate a reliable signature for the worm. Shield [34] uses transport layer filters to block the traffic that exploits a known vulnerability. Filters are exploit-independent, and vulnerabilities are described as a partial state machines of the vulnerable application. In [3], Christodorescu et al. proposed an instruction semantics based worm detection technique. The proposed approach can detect code polymorphism that uses instruction reordering, register shuffling, and garbage insertions. It is worth noting that unless the attacker combines the polymorphic blending attack proposed in this paper with other evasion techniques, the approaches cited above [1, 2, 3, 14, 20, 30, 34] may be able to detect the attack. We further discuss possible countermeasures against the polymorphic blending attack in Section 4.7.

A number of attacks aimed at evading Host-based anomaly IDS have been developed. Wagner et al. [33] and Tan et al. [29] presented mimicry attacks against the stide model [9] developed by Forrest et al. The main idea behind these mimicry attacks was to inject dummy system calls into an attack sequence to make the final system call sequence look similar to the normal system call sequence. As a defense against mimicry attacks as well as other *impossible path* attacks [7, 32], more advanced detection approaches (e.g., [6, 7]) were proposed, which use call stack information along with the system call sequences. Recently, a more sophisticated mimicry attack was proposed by Kruegel et al. [13], which can evade most system call based anomaly IDS.

Several application payload-based anomaly IDS [15, 18, 19] have been proposed which monitor the payload of a packet for anomalies. In [16], Kruegel et al. proposed four different models, namely, length, character distribution, probabilistic grammar, and token finder, for the detection of HTTP attacks. PAYL, proposed by Wang and Stolfo [35], records the average frequency of occurrences of each byte in the payload of a normal packet. A separate profile is created for each port and packet length. In their recent work [36], the authors suggested an improved version of PAYL that computes

several profiles for each port. At the end of the training, clustering is performed to reduce the number of profiles. They proposed that instead of byte frequency, one can also use an *n*-gram model in a similar fashion. One main drawback of the system is that they do not consider an advanced attacker, who may know the IDS running at the target and actively try to evade it. In this paper we provide strong evidence that such byte frequency based anomaly IDS are open to attacks and may be easily evaded.

CLET [5], an advanced polymorphic engine, comes closest to our polymorphic blending attack. It performs spectrum analysis to evade IDS that use data mining methods for worm detection. Given an attack payload, CLET adds padding bytes in a separate *cramming bytes* zone (of a given length) to try and make the byte frequency distribution of the attack close to the normal traffic. However, the encoded shellcode (using *XOR*) in CLET may still deviate significantly from the normal distribution and the obtained polymorphic attack may be detected by the IDS. A preliminary work by Kolesnikov et al. [12] introduced and cursorily explored polymorphic blending attacks. In this paper we present a systematic approach for evading byte frequency-based network anomaly IDS, and provide detailed analysis of the design, complexity and possible countermeasures for the polymorphic blending attacks. We also show that our polymorphic blending technique is much more effective than CLET in evading byte frequency-based anomaly IDS.

3 Blending Attacks

3.1 Polymorphism

A *polymorphic attack* is an attack that is able to change its appearance with every instance. Thus, there may be no fixed or predictable signature for the attack. As a result, it may evade detection because most current intrusion detection systems and anti-virus systems are signature-based. Exploit mutation and shellcode polymorphism are two common ways to generate polymorphic attacks. In general, there are three components in a polymorphic attack:

1. Attack Vector: an attack vector is used for exploiting the vulnerability of the target host. Certain parts of the attack vector can be modified to create mutated but still valid exploits. There might still be certain parts, called the invariant, of the attack vector that have to be present in every mutant for the attack to work. If the attack invariant is very small and exists in the normal traffic, then an IDS may not be able to use it as a signature because it will result in a high number of false positives.

2. Attack Body: the code that performs the intended malicious actions after the vulnerability is exploited. Common techniques to achieve attack body (shellcode) polymorphism include register shuffling, equivalent instruction substitution, instruction reordering, garbage insertions, and encryption. Different keys can be used in encryption for different instances of the attack to ensure that the byte sequence is different every time.

3. Polymorphic Decryptor: this section contains the part of the code that decrypts the shellcode. It decrypts the encrypted attack body and transfers control to it. Polymorphism of the decryptor can be achieved using various code obfuscation techniques.

Detection of Polymorphic Attacks All attack instances contain exploit code and/or input data that are typically not used in normal activities. For example, an attack instance, especially its decryptor and encrypted shellcode, may contain characters that have very low probability of appearing in a normal packet. Thus, an anomaly-based IDS can detect the polymorphic attack instances by recognizing their deviation from the normal profile. For example, Wang et al. [35, 36] showed that the byte frequency distribution of an (polymorphic) attack is quite different from that of normal traffic, and can thus be used by the anomaly-based IDS `PAYL` to detect simple polymorphic attacks. However, detection of a sophisticated polymorphic attack is much more challenging.

3.2 Blending Attacks

Clearly, if a polymorphic attack can "blend in" with (or "look" like) normal, it can evade detection by an anomaly-based IDS. Normal traffic contains a lot of syntactic and semantic information, but only a very small amount of such information can be used by a *high speed* network-based anomaly IDS. This is due to fundamental difficulties in modeling complex systems and performance overhead concerns in real-time monitoring. The network traffic profile used by *high speed* anomaly IDS, e.g., `PAYL`, typically includes simple statistics such as maximum or average size and rate of packets, frequency distribution of bytes in packets, and range of tokens at different offsets.

Given the incompleteness and the imprecision of the normal profiles based on simple traffic statistics, it is quite feasible to launch what we call *polymorphic blending attacks*. The main idea is that, when generating a polymorphic attack instance, care can be taken so that its payload characteristics, as measured by the anomaly IDS, will match the normal profile. For example, in order to evade detection by `PAYL` [35, 36], the polymorphic

attack instance can carefully choose the characters used in encryption and pad the attack payload with a chosen set of characters, so that the resulting byte frequency of the attack instance closely matches the normal profiles and thus will be considered normal by PAYL.

3.2.1 A Realistic Attack Scenario

Before presenting the general strategies and techniques used in polymorphic blending attacks, we present an attack scenario and argue that such attacks are realistic. Figure 1 shows the attack scenario that is the basis of our case study. There are a few assumptions behind this scenario:

- The adversary has already compromised a host X inside a network A which communicates with the target host Y inside network B. Network A and host X may lack sufficient security so that the attack can penetrate without getting detected, or the adversary may collude with an insider.
- The adversary has knowledge of the IDS (IDS_B) that monitors the victim host network. This might be possible using a variety of approaches, e.g., social engineering (e.g., company sales or purchase data), fingerprinting, or trial-and-error. We argue that one *cannot* assume that the IDS deployment is a secret, and security by obscurity is a very weak position. We assume IDS_B is a payload *statistics* based system (e.g., PAYL). Since the adversary knows the learning algorithm being used by IDS_B, given some packet data from X to Y, the adversary will be able to generate its *own* version of the *statistical* normal profile used by IDS_B.
- A typical anomaly IDS has a threshold setting that can be adjusted to obtain a desired false positive rate. We assume that the adversary does not know the exact value of the threshold used by IDS_B, but has an estimation of the generally acceptable false positive and false negative rates. With this knowledge, the adversary can estimate the error threshold when crafting a new attack instance to match the IDS profile.

We now explain the attack scenario. Once the adversary has control of host X, it observes the normal traffic going from X to Y. The adversary estimates a normal profile for this traffic using the same modeling technique that IDS_B uses. We call this an *artificial profile*. With it, the adversary creates a mutated instance of itself in such a way that the statistics of the mutated instance match the artificial profile. When IDS_B analyzes these mutated attack packets, it is unable to discern them from normal traffic because the artificial profile can be very close to the actual profile in use by IDS_B. Thus, the attack successfully infiltrates the network B and compromises host Y.

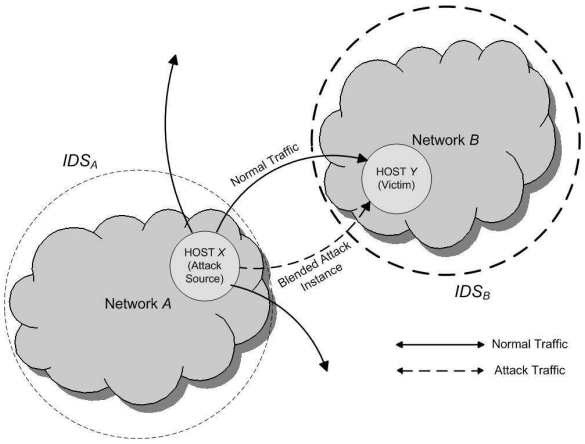


Figure 1: Attack Scenario of Polymorphic Blending Attack

3.2.2 Desirable Properties of Polymorphic Blending Attacks

Clearly, the key for a polymorphic blending attack to succeed in evading an IDS is to be able to learn an artificial profile that is very close to the actual normal profile used by the IDS, and create polymorphic instances that match the artificial profile. There are other desirable properties. First, the blending process (e.g., with encoding and padding) should not result in an abnormally large attack size. Otherwise, a simple detection heuristic will be to monitor the network flow size. Second, although we do not put any constraint on the resources available to the adversary, the polymorphic blending process should be economical in terms of time and space. Otherwise, it will not only slow down the attack, but also increase the chance of detection by the local IDS (e.g., IDS_A or host-based IDS.) More formally, given a description of the algorithm that the IDS uses to learn and match the normal profile and an attack instance, the time (and space) complexity of the algorithm used to apply polymorphic blending to the attack instance should be a small degree polynomial with respect to the initial attack size. Algorithms that require exponential time and space may not be practical. Since the learning time should be small, the blending algorithm should not require to collect a lot of normal packets to learn the normal statistics.

3.3 Steps of Polymorphic Blending Attacks

The polymorphic blending attack has three basic steps: (1) learn the IDS normal profile; (2) encrypt the attack body; (3) and generate a polymorphic decryptor.

3.3.1 Learning The IDS Normal Profile

The task at hand for the adversary is to observe the normal traffic going from a host, say X, to another host

in the target network, say Y, and generate a normal profile close to the one used by the IDS at the target network, say IDS_B, using the same algorithm used by the IDS.

A simple method to get the normal data is by sniffing the network traffic going from network A to host Y. This can be easily accomplished in a bus network. In a switched environment, it may be harder to obtain such data. Since the adversary knows the type of service running at the target host, he can simply generate normal request packets and learn the artificial profile using these packets.

In theory, even if the adversary learns a profile from just a single normal packet, and then mutates an attack instance so that it matches the statistics of the normal packet perfectly, the resulting polymorphic blended attack packet should not be flagged as an anomaly by IDS_B, provided the normal packet does not result in a false positive in the first place. On the other hand, it is beneficial to generate an artificial profile that is as close to the normal profile used by IDS_B as possible, so that if a polymorphic blended attack packet matches the artificial profile closely it has a high chance of evading IDS_B. In general, if more normal packets are captured and used by the adversary, she will be able to learn an artificial normal profile that is closer to the normal profile used by IDS_B.

3.3.2 Attack Body Encryption

After learning the normal profile, the adversary creates a new attack instance and encrypts (and blends) it to match the normal profile. A straightforward byte substitution scheme followed by padding can be used for encryption. The main idea here is that every character in the attack body can be substituted by a character(s) observed from the normal traffic using a substitution table. The encrypted attack body can then be padded with some more garbage normal data so that the polymorphic blended attack packet can match the normal profile even better. To keep the padding (and hence the packet size) minimal, the substituted attack body should already match the normal profile closely. We can use this design criterion to produce a suitable substitution table.

To ensure that the substitution algorithm is reversible (for decrypting and running the attack code), a one-to-one or one-to-many mapping can be used. A single-byte substitution is preferred over multi-byte substitution because multi-byte substitution will inflate the size of the attack body after substitution. An obvious requirement of such encryption scheme is that the encrypted attack body should contain characters from only the normal traffic. Although this may be hard for a general encryption technique (because the output typically looks random), it is an easy requirement for a simple byte substitution scheme. However, finding an optimal substitution table that requires minimal padding is a complex problem. In Section 4, we show that for certain cases this is a very hard problem. We can instead use a greedy method to find an acceptable substitution table. The main idea is to first sort the statistical features in the descending order of the frequency for both the attack body and normal traffic. Then, for each unassigned entry with the highest frequency in the attack body, we simply map it to an available (not yet mapped) normal entry with the highest frequency. This procedure is repeated until all entries in the attack body are mapped. The feature mapping can be translated to a character mapping and a substitution table can be created for encryption and decryption purposes.

3.3.3 Polymorphic Decryptor

A decryptor first removes all the extra padding from the encrypted attack body and then uses a reverse substitution table (or decoding table) to decrypt the attack body to produce the original attack code (shellcode).

The decryptor is not encrypted but can be mutated using multiple iterations of shellcode polymorphism processing (e.g., mapping an instruction to an equivalent one randomly chosen from a set of candidates). To reverse the substitution done during blending, the decryptor needs to look up a decoding table that contains the required reverse mappings. The decoding table for one-to-one mapping can be stored in an array where the i-th entry of the array represents the normal character used to substitute attack character i. Such an decoding table contains only normal characters. Unused entries in the table can be used for padding. On the other hand, storage of decoding tables for one-to-many mapping or variable-length mapping is complicated and typically requires larger space.

3.4 Attack Design Issues

3.4.1 Incorporating Attack Vector and Polymorphic Decryptor in Blending

We discussed in Section 3.3.2 that the encryption of the attack body is guided by the need to make the attack packet match the normal statistical profile (or more precisely, the learned artificial profile).

The attack vector, decryptor, and substitution table are not encrypted. Their addition to the attack packet payload alters the packet statistics. The new statistics may deviate significantly from the normal profile. In such a case, we must find a new substitution table in order to match the whole attack packet to the normal profile. First, we take the normal profile and subtract the frequencies of characters in the attack vector, decryptor, and existing substitution table. Next, we find a new substitution table using the adjusted normal profile. If the

statistics of the new substitution table is not significantly different from the old substitution table, we use the new substitution table for encryption. Otherwise we repeat the above steps.

3.4.2 Packet Length based IDS Profile

If IDS_B has different profiles for packets of different lengths, as in the case of PAYL, the substitution phase and padding phase need to use the normal profile corresponding to the final attack packet size. A target length greater than the length of the original attack packet (before polymorphic blending) is chosen at first. The encryption step is then applied and the packet is padded to the target length. If the statistics of the resulting attack packet is not very close to the normal profile, a different target length is chosen and the above process is repeated. Another strategy is to divide the attack body into multiple small packets and perform the polymorphic blending process for all of them separately.

4 Evaluation and Results

To demonstrate that polymorphic blending attacks are feasible and practical, we show how an attack can use polymorphic blending to evade the anomaly IDS PAYL.

In this section, we first describe the polymorphic blending techniques to evade PAYL. Then we report the results of the experiments we ran to evaluate the evasion capabilities of the polymorphic blending attacks.

In our evaluation, we first established a baseline performance by sending polymorphic instances (generated using the CLET polymorphic engine) of the attack to PAYL and verified that all of the instances were detected by the IDS as anomalies. Then, without changing the configuration of PAYL, we used our polymorphic blending techniques to generate attack instances to see how well they can evade the IDS.

4.1 PAYL Anomaly IDS as A Case Study

PAYL has been shown to be effective in detecting polymorphic attacks and worms [35, 36]. For this reason we used PAYL in our case study. We used the 2-gram version in addition to the 1-gram version to evaluate how polymorphic blending attack is affected when an IDS uses a more comprehensive model.

PAYL uses n-gram analysis by recording the frequency distribution of n-grams in the payload of a packet. A sliding window of width n is used to record the number of occurrences of all the n-grams present in the payload. A separate model is generated for each packet length. These models are clustered together at the end of the training to reduce the number of models. Furthermore, the length of a packet is also monitored for anomalies. Thus a packet with an unseen or very low frequency length is flagged as an anomaly. $\{f(x_i), \sigma(x_i)\}$ represents the PAYL model of normal traffic, where x_i is the ith gram, which is a character in 1-gram PAYL, and a tuple in 2-gram PAYL. $f(x_i)$ is the average relative frequency of x_i in the normal traffic, and $\sigma(x_i)$ is the standard deviation of x_i in the normal traffic. The anomaly score as calculated by PAYL is shown in Equation 1.

$$score(P) = \sum_i (\mathring{f}(x_i) - f(x_i))/(\sigma(x_i) + \alpha) \quad (1)$$

Here, P is the monitored packet, $\mathring{f}(x_i)$ is the relative frequency of the ith gram x_i in P, and α is a smoothing factor used to prevent division by zero. For convenience we will use the term frequency to denote relative frequency.

We evaluated our polymorphic blending attack with the first version of PAYL as described in [35]. Wang *et al*. [36] proposed some improvements on PAYL in their recent version. We believe that our attack still works for this new version of PAYL. The main improvement of the new version is to use multiple centroids for a given packet length, so that a low false positive rate can be achieved using a relatively low anomaly threshold. In this case, our polymorphic blending attack has to use the same learning algorithm as the new version of PAYL. Furthermore, more normal traffic needs to be used to learn an artificial profile that is close to the actual normal profile. Thus, the effect is that our attack may take a little more time. The new version also matches ingress *suspicious* traffic with egress *suspicious* traffic to find worms. This feature does not have any effect on our attack because the attack instances blend in with normal.

4.2 Evading 1-gram

To evade 1-gram PAYL, the frequency of each character in the attack packet should be close to the average frequency recorded during the learning phase. We substitute the characters in the attack packet with the characters seen in the normal traffic, and apply sufficient amount of padding so that the 1-gram frequencies of the resulting packet match the normal profile very closely. We first present analytical results on the amount of padding required to match the substituted attack body with the normal profile perfectly. Then we present a substitution algorithm that uses the padding criteria to minimize the amount of required padding.

In the following sections, we assume that the normal frequency $f(x)$ has already been adjusted for the attack vector, the decryptor, and the decoding table (as discussed in Section 3.4.1, these parts need to be accounted for when computing the frequencies of characters to find a suitable substitution).

4.2.1 Padding

Let $\hat{w}$ and $\acute{w}$ be the substituted attack body before and after padding, respectively. Let n be the number of distinct characters in the normal traffic. $\|s\|$ denotes the length of a string s, and λ_i denotes the number of occurrences of the normal character x_i in the padding section of the blending packet. Then,

$$\|\acute{w}\| = \|\hat{w}\| + \sum_{i=1}^{n} \lambda_i \tag{2}$$

Suppose the relative frequency of character x_i in the normal traffic and the substituted attack body is $f(x_i)$ and $\hat{f}(x_i)$, respectively. Since the final desired frequency of x_i is $f(x_i)$, the number of occurrences of x_i in the blending packet should be $\|\acute{w}\|f(x_i)$. Thus, λ_i can be defined using the following equation:

$$\lambda_i = \|\acute{w}\|f(x_i) - \|\hat{w}\|\hat{f}(x_i), \quad 1 \leq i \leq n \tag{3}$$

Equation 3 can be re-written as,

$$\|\acute{w}\| = \frac{\lambda_i + \|\hat{w}\|\hat{f}(x_i)}{f(x_i)}, \quad 1 \leq i \leq n \tag{4}$$

Since $f(x)$ and $\hat{f}(x)$ are relative frequency distributions, $\sum_i f(x_i) = \sum_i \hat{f}(x_i) = 1$. Unless they are identical, there exists some character x_i for which $\hat{f}(x_i) > f(x_i)$. The character x_i is perhaps "overused" in the substituted attack body. It is trivial to see that we need to pad all the characters except the one that is most overused. Let x_k be the character that has highest overuse and δ be the degree of overuse. That is,

$$\delta = \delta_k = max_i\{\delta_i\}, \text{ where } \delta_i = \frac{\hat{f}(x_i)}{f(x_i)}, \quad 1 \leq i \leq n \tag{5}$$

Since no padding is required for character x_k, $\lambda_k = 0$. Putting this value in Equation (4) we get:

$$\|\acute{w}\| = \frac{0 + \|\hat{w}\|\hat{f}(x_k)}{f(x_k)} = \delta\|\hat{w}\| \tag{6}$$

The amount of padding required for each character x_i can be calculated by substituting the value of $\|\acute{w}\|$ in Equation (3):

$$\lambda_i = \|\hat{w}\|(\delta f(x_i) - \hat{f}(x_i)) \tag{7}$$

Thus, using the padding defined by the above equation, we can match the final attack packet perfectly to the normal frequency $f(x)$. Furthermore, the amount of padding required by the above equation is the minimum amount that is needed to match the normal profile exactly. Please refer to Appendix 6.1 for the proof.

4.2.2 Substitution

The analysis in Section 4.2.1 shows that the amount of padding can be minimized by minimizing δ, which is $max(\frac{\hat{f}(x_i)}{f(x_i)})$. This in turn means that the objective of the substitution process is to minimize the resulting δ. There are two possible cases for substitution. The first is when the number of distinct characters present in the attack body (m) is less than or equal to the number of distinct characters present in the normal traffic (n), i.e. $m \leq n$. In this case we can perform single-byte encoding, either one-to-one or one-to-many. If $m > n$, we need to use multi-byte encoding.

Case: $m \leq n$ We suggest a greedy algorithm to generate a one-to-many mapping from the attack characters to the normal characters that provides an acceptable solution and is computationally efficient. Our algorithm tries to minimize the ratio δ locally for each substitution assignment.

Let x_i represents a normal character and y_j represent an attack character. Let $f(x_i)$ be the frequency of character x_i in normal traffic and $g(y_j)$ be the frequency of character y_j in the attack body. Let $S(y_j)$ be the set of normal characters to which y_j is mapped. Let $\hat{tf}(y_j) = \Sigma_{x_i \in S(y_j)} f(x_i)$. The probability that y_j is substituted by $x_i, x_i \in S(y_j)$, during substitution is $\frac{f(x_i)}{\hat{tf}(y_j)}$. Thus, the number of occurrences of x_i in the substituted attack body is $\frac{f(x_i) \times g(y_j)}{\hat{tf}(y_j)}$. We then have $\delta_i = \frac{(f(x_i) \times g(y_j)/\hat{tf}(y_j))}{f(x_i)} = \frac{g(y_j)}{\hat{tf}(y_j)}$. Our greedy algorithm tries to minimize this ratio δ_i locally. The substitution algorithm is as follows.

Sort the normal character frequency $f(x)$ and the attack character frequency $g(y)$ in descending order. For the first m characters, map y_i to x_i and set $S(y_i) = \{x_i\}$ and $\hat{tf}(y_i) = f(x_i), \forall 1 \leq i \leq m$. For the $(m+1)th$ normal character, x_{m+1}, find an attack character (y_j) with maximum ratio of $\frac{g(y_j)}{\hat{tf}(y_j)}$. Assign x_{m+1} to y_j and set $S(y_j) = \{x_{m+1}\} \cup S(y_j)$ and $\hat{tf}(y_j) = \hat{tf}(y_j) + f(x_{m+1})$. This is performed for each of the remaining characters until we reach the end of the frequency list $f(x)$. While substituting alphabet y_j in the attack body, we choose a character x_i from the set $S(y_j)$ with probability $\frac{f(x_i)}{\hat{tf}(y_j)}$.

Consider an example where $f(a,b,c) = \{0.3, 0.4, 0.3\}$, attack body $w = qpqppqpq$, and $g(p,q) = \{0.5, 0.5\}$. According to the above algorithm, initially, b and a are assigned to p and q respectively. At this point, ratio $\frac{g(p)}{\hat{tf}(p)} = 1.25$ and $\frac{g(q)}{\hat{tf}(q)} = 1.66$. So we assign c to q. Thus, p will be substituted by b and q will be substituted by a with probability 0.5 and by c with probability 0.5. Thus, the attack after substitution can be

$\hat{w} = cbabbcba$.

In our experiments, we used a simple one-to-one mapping where characters with the highest frequencies in the attack packet are mapped to characters with the highest frequencies in normal traffic. This simple mapping is shown to be sufficient for the blending purpose.

Case: $m > n$ We suggest a heuristic based on Huffman encoding scheme to obtain a small attack size after encoding. Given the frequency distribution of the characters in the attack body being encoded, Huffman encoding provides a minimum length packet after encoding. The weights of the nodes in Huffman tree is the sum of the relative frequencies of all its descendant leaf nodes. The weight of a leaf node is the frequency of a given character in the attack body. Every edge in the tree is assigned to a character from the normal profile. In the original Huffman coding the edges of the Huffman tree are labeled randomly. Random labeling of the edges may give us a very large value of δ. We developed a heuristic to assign labels to edges of Huffman tree to find a mapping that gives us a very small δ. Before stating the heuristic, we present the problem of optimally assigning the labels to the edges in Huffman tree:

Given a Huffman tree, assign labels $l(v) \in N$ to the vertices v in the tree, such that after substitution, $\delta = max(\frac{\hat{f}(x)}{f(x)}), \forall x \in N$, is minimum. The constraint on the label $l(v)$ is that if $parent(v_1) = parent(v_2)$, then $l(v_1) \neq l(v_2)$.

We propose a greedy algorithm to find an approximate solution for the above problem. First sort the vertices in descending order of their weight and initialize the capacity of each character $cap(x_i) = f(x_i), \forall x_i \in N$. Then starting from the leftmost unlabeled vertex v_j, find a character x_i with the maximum $cap(x_i)$ and that is not assigned to any of the direct siblings of v_j. Assign x_i to v_j and reduce the capacity of x_i by the weight of the vertex. Repeat until all the vertices are assigned. The labels generated by the above algorithm are used for the substitution process. An example is explained in Figure 2.

4.3 Evading 2-gram

The 1-gram PAYL model assumes that the bytes occurring in the stream are independent. It does not try to capture any information of byte sequencing of the normal traffic. The 2-gram model on the other hand can capture some byte sequencing information. It records the frequencies of all the 2-grams present in the normal traffic. It is easy to see that by matching 2-grams we are inherently performing 1-gram matching as well.

For 2-gram, the polymorphic blending process needs to match the frequencies of not only all the characters but also all the tuples. Similar to 1-gram substitution,

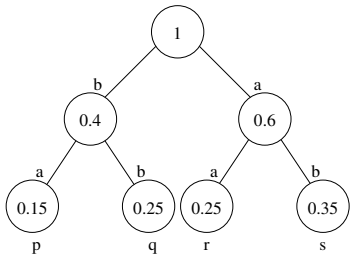


Figure 2: 1-gram multibyte encoding. The frequency of the normal character is $f(a, b) = \{0.5, 0.5\}$. Sorted weights of the nodes are $\{0.6, 0.4, 0.35, 0.25, 0.25, 0.15\}$. Using the proposed algorithm we get $S : \{p, q, r, s\} \mapsto \{ba, bb, aa, ab\}$

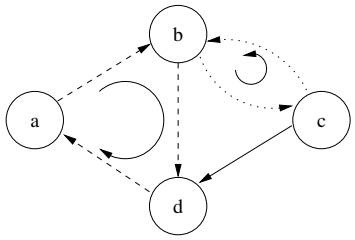


Figure 3: 2-gram multibyte encoding. $e_0 = da,\ e_1 = bc$. $w = 01101010$. $\hat{w} = bdabcbcbdabcbdabcbda$

one can either use single-byte encoding or multi-byte encoding for substitution. For single-byte encoding, the goal is to find a one-to-one or one-to-many mapping that ensures that all the tuples in the substituted attack body are also present in normal profile. In Appendix 6.2, we show that this is NP-complete for the general case by reducing the well known sub-graph isomorphism problem [4] to the mapping problem. Unlike single-byte encoding, it is possible for an attacker to find a multi-byte encoding scheme that produces only valid 2-grams. Here, we present a viable multi-byte encoding scheme.

4.3.1 Multi-byte Encoding

A 2-gram normal profile can be viewed as a Moore machine (FSM) which has a state for each character in N. Every state is a start state and end state. A transition from state v_1 to state v_2 exists if and only if 2-gram v_1v_2 exists in normal profile. This FSM represents the language accepted by the IDS with given 2-gram profile. Strings generated by the FSM contain only normal 2-grams. Characters in an attack body can be mapped to paths in this FSM. For example, suppose the state machine has two cycles reachable from each other. e_1 and e_2 be two edges such that e_1 is present only in the first cycle and e_2 is present only in the second cycle. Given a bit representation of the attack body, we can encode 0 using e_0 and 1 using e_1. We can generate any bit string represented using these two tuples interleaved

by other non-informative characters present in the cycles and in the paths between two cycles. Figure 3 shows an example of such an encoding scheme. Such an encoded attack string will have a very large size. We use it to show the existence of an encoding scheme that is able to match the normal 2-grams. We can generate a more efficient encoding scheme by using the entropy measure of transitions at each state. The complete details of such an encoding scheme are not addressed in this paper. The authors suggest readers to refer to coding theory for more on entropy based encoding.

4.3.2 Approximate Single-Byte Encoding

As discussed above, the problem of finding a single-byte substitution is hard for 2-gram. On the other hand, multi-byte encoding may increase the size of the attack packets considerably. We can use a simple approximation algorithm to find a good one-to-one substitution. The algorithm performs single byte substitution in such a way that tuples with high frequencies in the attack packet are greedily matched with tuples with high frequencies in normal traffic.

The details of the algorithm are as follows. First, sort the normal tuple frequencies $f(x_{i,j})$ and the attack tuple frequencies $g(y_{i,j})$ in descending order. Initially, all tuples in the list $f(x_{i,j})$ are marked $unused$ and the substitution table is cleared. The frequency list $g(y)$ is traversed from the top. For every tuple $y_{i,j}$ in the sorted attack tuple list, the list $f(x)$ is traversed from the beginning to find an $unmarked$ tuple $x_{i',j'}$ so that substituting y_i with $x_{i'}$ and y_j with $x_{j'}$ does not violate any mappings that were already made. The tuple $x_{i',j'}$ is $marked$ and the substitution table is updated. The above algorithm is fast and provides consistent reversible matching. The algorithm does not guarantee to provide the best substitution, i.e., the closest distance to the target frequency distribution.

4.3.3 Padding

We introduce an efficient padding algorithm that does not provide minimal padding but tries to match the target distribution in a greedy manner. Let $d_f(x_{i,j})$ be the difference between the frequency of tuple $x_{i,j}$ in the normal profile and the substituted attack body. Find a tuple $x_{k,l}$ from the list of normal tuples that starts with the last padded character (x_k) and that has the highest $d_f(x_{k,m}), \forall 1 \leq m \leq 256$. The second character of the tuple, x_l, is padded to the end of the packet and $d_f(x_{k,l})$ is reduced. This step is repeated until the blending attack size reaches a desired length.

4.4 Complexity of Blending Attacks

We now summarize the methods provided above and analyze the hardness of a polymorphic blending attack while keeping the design goals (Section 3.2.2) in mind. For 1-gram blending, although finding a substitution that minimizes the padding seems to be a hard-problem and may take exponential time, we have proposed greedy algorithms that find a good substitution that require small amount of padding to perfectly match the normal byte frequency. For 2-gram blending, finding a single-byte substitution that ensures only normal tuples after substitution is shown to be NP-hard (see the proof in Appendix 6.2). An approximation algorithm can be used to efficiently compute a substitution that may introduce a few invalid tuples. A multibyte encoding scheme can achieve a very good match with no invalid tuples at the expense of very large attack sizes. An attacker has to therefore consider several trade-offs between the degree of matching, attack size, and time complexity to mount successful blending attacks.

4.5 Experiment Setup

4.5.1 Attack Vector

We chose an attack that targets a vulnerability in Windows Media Services (MS03-022). The attack vector we selected exploits a problem with the logging ISAPI extension that handles incoming client requests. It is based on the implementation by `firew0rker` [8]. The size of the attack vector is 99 bytes and is required to be present at the start of the `HTTP` request. The attack needs to send approximately 10KB of data to cause the buffer overflow and compromise the system. Our attack body opens a `TCP` client socket to an IP address and sends system registry files. The size of the unencrypted attack body is 558 bytes and contains 109 different characters. During the blending process, we divided our attack into several packets. If our final blending attack after padding does not add up to 10KB, we just send some normal packets as a part of the attack to cause the buffer overflow. The decryptor was divided into multiple sections and distributed among different packets. The attack body was divided among all the attack packets.

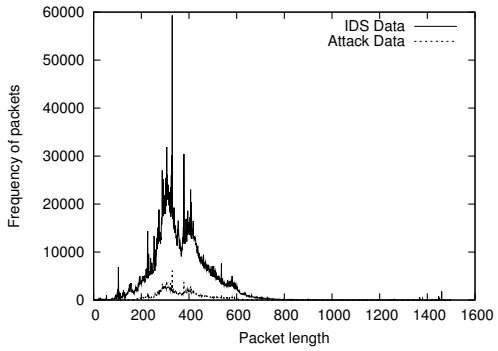


Figure 4: Packet length distribution

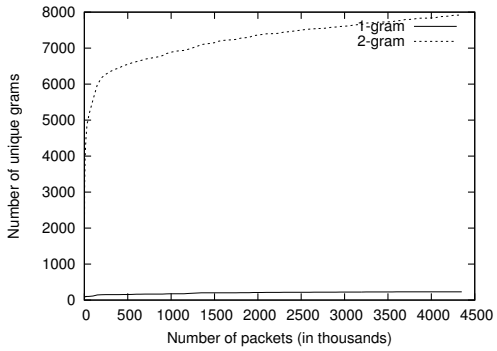


Figure 5: Observed Unique 1-grams and 2-grams

4.5.2 Dataset

Data Type	Feature	Packet length		
		418	730	1460
IDS Training	Num. of Pkts	16,490	540	1,781
	One Grams	106	90	128
	Two Grams	4,325	3,791	3,903
Attack Training	Num. of Pkts	2,168	82	249
	One Grams	89	86	86
	Two Grams	2,847	2,012	2,196

Table 1: HTTP Traffic dataset

We collected around 15 days of HTTP traffic coming to our department's network in November 2004. We used several IDSs, including *Snort*, to verify that this data contains no known attack. We removed all the packets with no TCP payload. We used the data of the first 14 days (4,356,565 packets, 1.9GB) for IDS training to obtain the IDS normal profiles. A separate profile was created for each TCP payload length (or simply packet length). The full payload section of each packet was used to compute the profiles. The last day of the HTTP traffic was made available to the attacker to learn the artificial profile. We also used cross-validation, i.e., randomly picking one of the 15 days for attack training and the rest for IDS training, to verify the results of our experiments.

The packet length distributions in the IDS training dataset and the attack training dataset are shown in Figure 4. Among this packet lengths, we chose three different lengths to implement the blending attack, namely 418, 730 and 1460. These packets lengths are large enough to accommodate the attack data into a small number of packets. These lengths also occurred frequently in the training dataset. A separate artificial profile was created for each packet length using the attack training data of the same packet length. Thus, we generated three 1-gram models and three 2-gram models for different packet lengths. Table 1 shows the details of the datasets used for the evaluation. The numbers of unique 1-grams and 2-grams in the data are also shown in the table.

4.6 Evaluation

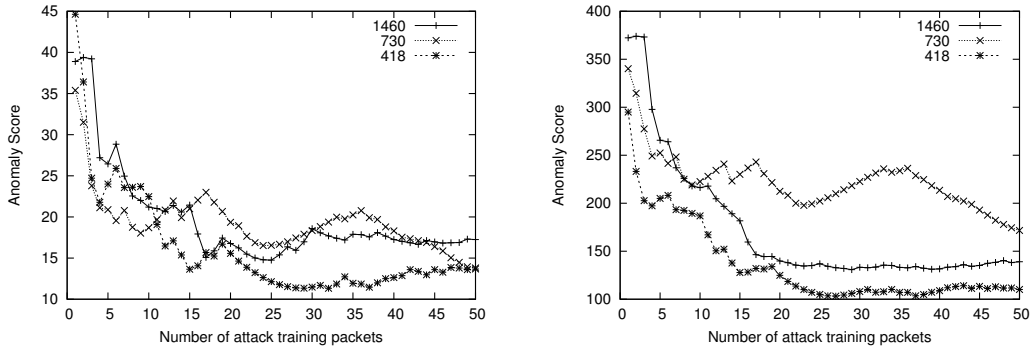
Training time of 1-gram and 2-gram PAYL: We performed experiments on the training time required to learn the profiles used by PAYL. Figure 5 shows the numbers of unique 1-grams and 2-grams observed in HTTP traffic stream. Since the numbers of observed 1-gram and 2-gram continue to increase as new packets arrive in the stream, the training of profiles for 1-gram and 2-gram takes a long time to converge. We trained our IDS model using all of the available IDS training data.

Traditional polymorphic attacks: To the best of our knowledge, CLET [5] is the only publicly available tool that implements evasion techniques against byte frequency-based anomaly IDS. For this reason we used CLET as our baseline. As mentioned in Section 2, given an attack CLET adds padding bytes in the payload to make the byte frequency distribution of the attack close to the normal traffic. However, CLET does not apply any byte substitution technique (see Section 4.2.2). Further, CLET does not address the evasion of 2-gram PAYL explicitly. We also generated polymorphic attacks using other well known tools (e.g., ADMutate [17]), and verified that they are less effective than CLET in evading PAYL.

We generated multiple polymorphic instances of our attack body using CLET and tested them against PAYL. Each attack instance contained one or more attack packets of given length. Different amount of bytes were crammed (padded) to obtain the desired attack size. Attack training data was used to generate spectral files used for cramming by the CLET engine. A polymorphic attack instance will evade an IDS model if and only if all the attack packets corresponding to the attack instance are able to evade the IDS. Thus, the anomaly score of an attack instance was calculated as the highest of all the anomaly scores (Equation 1) obtained by the attack packets corresponding to the attack instance. Table 2 shows the anomaly threshold setting of different PAYL models that result in the detection of all the attack instances. The anomaly thresholds were calculated as the minimum anomaly score over all the attack instances. Using the given thresholds, both 1-gram and 2-gram PAYL were successful in detecting all the instances of the attack. Having established this "baseline" performance, we would like to show that our blending attacks can evade PAYL even if a lower threshold is used.

Packet Length	1-gram	2-gram
418	872	1,399
730	652	1,313
1460	355	977

Table 2: IDS anomaly threshold setting that detects all the polymorphic attacks sent by the CLET engine



(a) 1-gram (b) 2-gram

Figure 6: Anomaly score of Artificial Profile

Packet Length	1-gram	2-gram
418	8	20
730	8	18
1460	14	40

Table 3: Number of packets required for the convergence of attacker's training

4.6.1 Artificial Profile

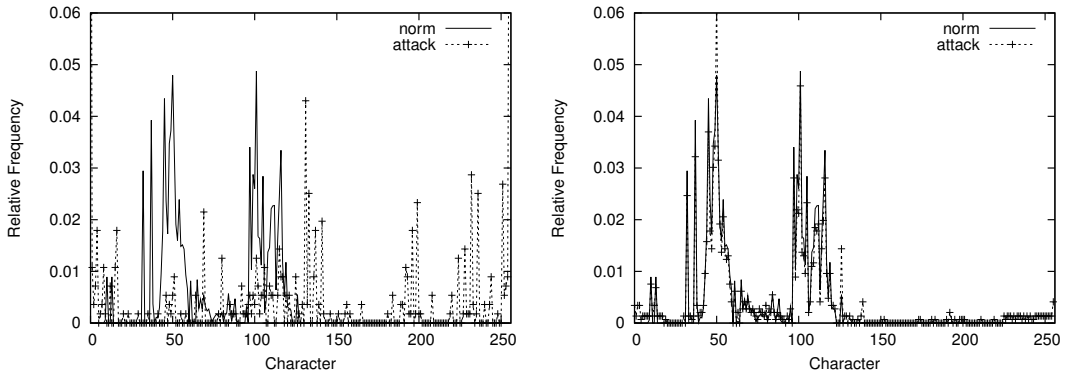
We used a simple convergence technique, similar to PAYL, to stop the training of the artificial profile. At every certain interval (convergence check interval) we check if the $Manhattan$ [1] distance between the artificial profiles at the last interval and the current interval is smaller than a certain threshold (convergence threshold). It stops training if the distance is smaller than the threshold. We set the convergence threshold ($= 0.05$) to be the same as the original implementation of PAYL. The artificial profile does not have to become very stable or match the normal profile perfectly because some deviation from the normal profile can be tolerated. To reduce the training time we set the convergence check interval to 2 packets. Thus, if we see two consecutive packets of a given length that are close to the learned profile, we stop training. Table 3 shows the number of packets required to converge the artificial profile of different packet lengths. As expected, the artificial profile converges very fast. The 1-gram profile converges faster than the 2-gram profile for the same packet length. We show that a small number of packets are enough to create an effective polymorphic blending attack. In practice, the attacker can use more learning data to create a better profile.

Figure 6 shows the anomaly score of the artificial normal profile, as calculated by the IDS normal profile, versus the number of attack training packets used to learn the artificial profile. As the number of attack training packets increases, the anomaly score of artificial normal profile decreases, which means that the artificial profile trained using more packets is a better estimation of the PAYL normal profile. The score needs to be less than the anomaly threshold of PAYL for the blending attack packets to have a realistic chance of evading PAYL. For all attack training sizes shown in Figure 6, the score is well under the threshold (Table 2) used to configure PAYL to detect all the traditional (without blending) polymorphic attack instances.

4.6.2 Blending Attacks for 1-gram and 2-gram PAYL

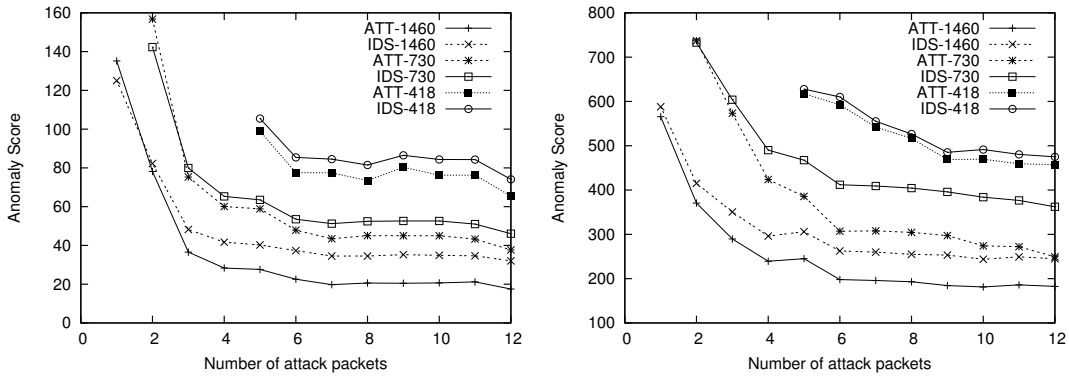
For each packet length, we generated both the 1-gram and 2-gram PAYL normal profiles using the entire IDS training dataset (i.e., the first 14 days of HTTP traffic). For each packet length, the 1-gram and 2-gram artificial normal models were learned using a fraction of the attack training dataset. The learning stops at the point the models converge, as shown in Table 3.

We used the one-to-one single-byte substitution technique discussed in Section 4.2.2 for constructing the blending attack against 1-gram PAYL, and the single byte encoding scheme discussed in Section 4.3.2 for the blending attack against 2-gram PAYL. Two sets of blending experiments were performed. In the first set of experiments, the substituted attack body was divided into multiple packets and each packet was padded separately to match the normal profile. A single decoding table is required to decode the whole attack flow. In the second set of experiments, the attack body was first divided into a given number of packets. Each of the attack body sections were substituted using one-to-one single byte substitution and then padded to match the normal frequency. Individually substituting the attack body for each packet allowed us to match the statistical profile of the substituted attack body closer to the normal profile. But it requires a separate decoding table for each packet, thus reducing the padding space considerably. For convenience, we call the first set of experiments



(a) Original attack packet (b) 1-gram Blending Packet for packet length 1460

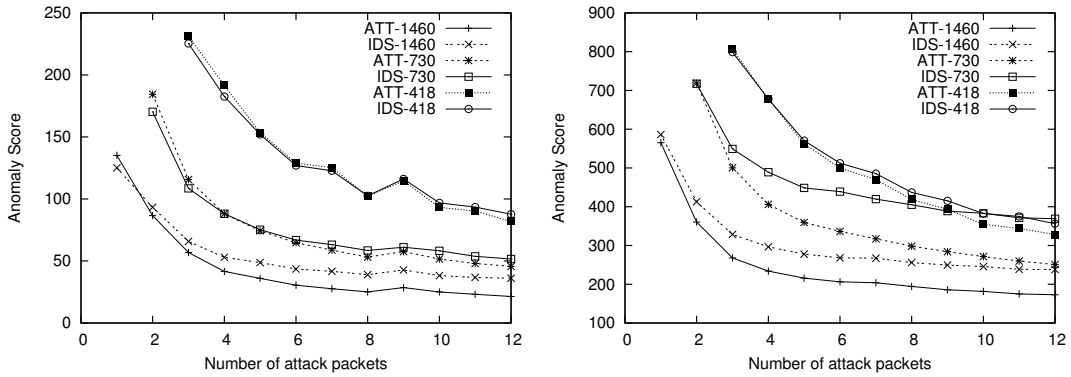
Figure 7: Comparison of frequency distribution of normal profile and attack packet



(a) 1-gram (b) 2-gram

Figure 8: Anomaly score of the blending attack packets (with local substitution) for artificial profile and IDS profile

global substitution, and the second *local substitution*. If $m > n$ for any of the above experiments, we simply substituted the low frequency attack characters using non-existing characters in the normal. This increased the error in blending attack but reduced the complexity of the blending attack algorithm. Figure 7 shows the comparison of the frequency distribution of different characters present in the HTTP traffic. The byte frequency distribution of the original attack instance is very different from the normal profile because the normal data has mainly printable ASCII characters whereas the attack payload has many characters that are unprintable. Thus, this was easily detected by both 1-gram and 2-gram IDS models. The attack was substituted and padded to obtain a single packet of length 1460. As shown in Figure 7(b), the frequency distribution of attack payload after substitution and padding becomes almost identical to the `PAYL` normal profile. This demonstrates the effectiveness of our polymorphic blending techniques. We studied how dividing an attack instance into several packets and blending them separately help match the attack packets with the artificial profile and evade `PAYL`. The experiments were performed with the number of attack packets ranging from 1 to 12. We checked the anomaly score of each attack packet as calculated by both the artificial profile and the IDS profile. Similar to the anomaly score of attack instances generated by CLET, the anomaly score of a blending attack instance was calculated as the highest of all the scores obtained by the attack packets corresponding to the blending attack instance. Figure 8 and Figure 9 show the anomaly scores of blending attacks with local substitution and global substitution, respectively. For each attack flow, we show the score of the packet with the highest score. It is evident that if the attack is divided into more packets, it matches the profile more closely. The reason is that if the attack body is divided into multiple fragments, for each packet there is more padding space available to match the profile. Also, local substitution works better than global substitution scheme for all cases except for 2-gram blending for packet length 418. Since our substitution table contains only normal 1-grams but may contain foreign 2-grams, a large substitution table may produce a large error for the 2-gram model. Considering



(a) 1-gram (b) 2-gram

Figure 9: Anomaly score of the blending attack packets (with global substitution) for artificial profile and IDS profile

that small packets have small padding space to reduce the error caused by the substitution table, having an individual substitution table in each packet can cause large error.

Although the score of the blending attack as calculated by the IDS model is greater than the score calculated by the artificial normal profile, it is still much lower than the anomaly threshold set for the detection of traditional polymorphic attacks.

Thus, our experiment clearly shows that unlike traditional polymorphic attacks, our blending attack is very effective in evading 1-gram and 2-gram PAYL for all the packet lengths and number of attack packets.

4.6.3 IDS False Positive Rate And Its Impact on Blending Attacks

We also studied the effect of false positive rates on the detection of blending attacks. Anomaly threshold for a given false positive rate (fp) is set such that only fp fraction of normal data has anomaly score higher than the anomaly threshold. The anomaly thresholds for different false positive rates are shown in Table 4. The number of attack packets required to evade the IDS successfully for a given threshold is shown in the parenthesis. As we increase the false positive rate, we need to divide the attack into more packets to keep the score below the anomaly threshold. Thus, keeping a high false positive rate may increase the size of the blending attack. From the table we can infer that even if the IDS keeps its false positive rate high to detect more attacks, blending attack can still easily evade it using an attack size as small as 3,650, i.e. five packets of length 730.

Since 2-gram PAYL records some sequence information along with byte frequencies, it seems to be a good representation of normal traffic. In our experiments we found that 2-gram PAYL consistently produces higher anomaly score than 1-gram PAYL for all attack packet lengths. But at the same time, the 2-gram IDS needs to set very high anomaly thresholds to avoid high false positive rates. Thus, in practice, the 2-gram PAYL is actually only marginally more effective than the 1-gram version in detecting attacks.

Blending attacks can be successfully launched on both 1-gram and 2-gram models. Larger packet lengths are more suitable for blending attacks. With few exceptions, the local substitution scheme works better than the global substitution scheme. The 2-gram model provides only marginal advantage over the 1-gram model in detecting blending attacks but requires huge space to store the model. Thus, the 2-gram model may not be a better choice over the 1-gram model.

4.7 Countermeasures

The experimental results reported above show that the statistical models used by PAYL are not sufficiently accurate to detect deliberate evasion attempts. We believe this problem is common to other network anomaly IDS that use traffic statistics [15, 18]. By following the ideas presented in this paper, it may be fairly easy to devise different blending algorithms in order to evade other network anomaly IDSs that rely solely on some form of packet statistics. The reason is that traffic statistics used by such network-based anomaly IDS do not provide a comprehensive representation of normal traffic. Application syntax and semantics related information cannot be modeled accurately using simple statistics of network packets. On the other hand, some of the IDS introduced in Section 2, e.g., [1, 2, 30], use syntax and semantics related information and could be used to detect the polymorphic blending attack. Nevertheless, modeling application syntax and semantic information is in general more expensive than measuring simple traffic statistics. Thus the trade-off between detection accuracy, hardness of evasion and operational speed has to be considered. A key direction to explore is to develop a more efficient semantic-based IDS that can be deployed on high-speed

False Positive	418		730		1460	
	1-gram	2-gram	1-gram	2-gram	1-gram	2-gram
0.1	61.07 (17,-)	373.4 (-,12)	63.70 (5,7)	467.6 (5,5)	74.50 (3,3)	447.7 (2,2)
0.01	78.61 (12,15)	456.9 (22,8)	143.6 (2,3)	625.5 (3,3)	81.98 (3,3)	531.0 (2,2)
0.001	125.5 (5,7)	561.8 (7,6)	164.6 (2,3)	670.5 (3,3)	239.2 (1,1)	931.9 (1,1)
0.0001	166.8 (5,5)	582.6 (7,5)	244.5 (2,2)	805.0 (2,2)	243.4 (1,1)	935.0 (1,1)

Table 4: Anomaly thresholds for different false positive rates in IDS models. Bracketed entries are the the numbers of packets required to evade the IDS using the local and global substitution scheme, respectively.

networks.

Another defense approach is to use multiple IDS models that use independent features. Such a collective set of models may be a better representation of the normal traffic. In such a case, a polymorphic blending attack will need to evade all (or the majority) of the models.

One reason blending attacks work is that the attacker has the complete knowledge of the IDS model being used. This gives the attacker an enormous advantage. A possible countermeasure is to introduce randomness [27] in the IDS model. Consider a model constructed by measuring the occurrence frequency of pairs of non-consecutive bytes that are separated by ν number of bytes. For example, given a payload containing the sequence of byte values $\{b_1, b_2, \cdots, b_l\}$, the IDS could measure the occurrence frequency of the pair of byte values $(b_i, b_{i+\nu+1}), \forall i = 0, \cdots, (l - \nu - 1)$, where l is the payload length. We call this a 2_ν-gram model. For $\nu = 0$, the 2_ν-gram model is the same as the 2-gram PAYL model. If the IDS chooses ν at random during the training phase, this makes the blending attack more difficult given that the attacker needs to guess the value of ν before applying the blending algorithm (note that ν is chosen at random before the model is created and is fixed for each packet. Therefore, the 2_ν-gram model is as complex as the 2-gram model used by PAYL). Furthermore, the IDS could construct m different models, each of them having a different randomly chosen ν_k, with $k = 1, \cdots, m$, and combine their output in order to obtain a more accurate decision about the packets. In this case the attacker needs to guess m values for the parameter ν and needs to devise a blending algorithm that "satisfies" all the m different models at the same time. This means that even if the attacker knows exactly how the IDS performs the training and test phases, it is much more difficult to evade it.

Preliminary experimental results show that if ν is small with respect to the payload size, the 2_ν-gram model is able to capture a sufficient amount of structural information that allows to construct an accurate IDS model. Further, the combination of different 2_ν-gram models appears to be a promising technique. However, the complexity of the detection system grows linearly with m. A thorough analysis of this modeling technique is beyond the scope of this paper and will be the subject of our future work.

While countermeasures may make evasion harder to succeed, they typically require more resources and can be more complex in design and implementation. It may also produce higher error rates if the IDS uses too many features such that its models "overfit" the data. In short, trade-offs between "hardness of evasion" and other performance measures need to be carefully considered.

5 Conclusion

In this paper, we presented a new class of attacks called polymorphic blending attacks. Existing polymorphic techniques can be used for evading signature-based IDS because the attack instances do not share a consistent signature. But anomaly IDS can detect these attack instances because the polymorphism techniques fail to mask their statistical anomalies. Our proposed attack overcomes this very shortcoming. The idea is to first learn the normal profiles used by the IDS, and then, while creating a polymorphic instance of an attack, make sure that its statistics match the normal profiles.

We described the basic steps and general techniques that can be used to devise polymorphic blending attacks. We presented a case study using the anomaly IDS PAYL to demonstrate that these attacks are practical and feasible. Our experiments showed that polymorphic blending attacks can evade PAYL while traditional polymorphic attacks cannot. We also showed that an attacker does not need a large number of packets to learn the normal profile and blend in successfully. The results with 2-gram PAYL suggested that simply using more complex features or models do not always provide a good defense against these polymorphic blending attacks. We discussed some possible defenses against polymorphic blending attacks.

Acknowledgments

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Notes

[1] Used by authors of PAYL to compare two models for convergence

6 APPENDIX

6.1 Proof of Optimal Padding for 1-gram Blending Attack

We prove that the padding calculated using Equation (7) is minimum for matching the 1-gram profile exactly.

Theorem 6.1 $\lambda_i \geq 0, \forall 1 \leq i \leq n$

Proof We prove the theorem by contradiction. Assume that for some j, $\lambda_j < 0$. Then from Equation (7), $\|\hat{w}\|(\delta f(x_j) - \hat{f}(x_j)) < 0$. Thus, $\delta < \frac{\hat{f}(x_j)}{f(x_j)}$. This contradicts Equation (5), therefore, all $\lambda_i \geq 0$. ∎

The frequency of a character x_i in the packet after padding is $\acute{f}(x_i) = \frac{\|\hat{w}\|\hat{f}(x_i)+\lambda_i}{\|\acute{w}\|}$. Using Equation (7) and Equation (4), $\acute{f}(x_i) = f(x_i)$. Thus, the final attack packet after padding has the exact target distribution, $f(x_i)$.

Theorem 6.2 *The padding calculated using Equation (7) is the minimum required padding to match frequencies exactly.*

Proof Suppose we perform padding using Equation (7). Suppose there exists another packet (say p, $\|p\| < \|\hat{w}\|$) with smaller padding and matches the frequencies exactly. Since $\lambda_k = 0$, the number of occurrences of x_k in p cannot decrease. Thus, frequency of x_k in packet p is $f_p(x_k) = \frac{\|\hat{w}\|\hat{f}(x_k)}{\|p\|} = \frac{\|\acute{w}\|f(x_k)}{\|p\|} > f(x_k)$. Thus, packet p does not match the normal frequencies exactly. Thus, we have reached a contradiction. ∎

6.2 Proof of Hardness of 2-gram Single-Byte Encoding

First, we look at the problem of evading a simple IDS that stores all the 2-grams present in the normal stream. While monitoring, it checks if all the 2-grams present in the traffic are also present in the normal 2-gram list. In the event that the IDS finds a 2-gram that was not present in normal traffic, IDS raises an alarm. Blending the attack packet with the normal traffic requires the attacker to transform the packet such that all the 2-grams in the packet after substitution are also present in the normal 2-gram list. Matching the frequencies of the tuples is at least as hard as the above simplified problem.

Suppose we have a normal traffic profile (N, T_N) and an attack packet description (M, T_M), where N and M is the set of normal and attack characters, respectively. T_N and T_M is the set of different 2-grams present in normal traffic and the attack, respectively. Also, the attacker is allowed to do only one-to-one substitution from M to N. Then, blending of the packet translates to finding a substitution S such that all the tuples in $S(w)$ are also present the normal profile. That is if $a_1a_2 \in T_M$, then $S(a_1a_2) \in T_N$.

Theorem 6.3 *The problem of finding a one-to-one substitution S to match 2-grams is NP-complete.*

Proof To prove that the problem is in NP-complete, we need to show that the problem is polynomial time verifiable and NP-hard.

Given a solution substitution S for the 2-gram matching problem, we can calculate $S(w)$ in $O(\|w\|)$ steps. For each 2-gram present in $S(w)$, checking if it is present in T_N can be done in $O(\|w\|.T_M)$ steps. Thus, this problem is poly-verifiable and consequently in NP.

To show that the problem is NP-hard, we reduce the problem of sub-graph isomorphism to substitution problem. A sub-graph isomorphism problem is that given two graphs $G(V, E)$ and $G'(V', E')$, decide whether G' is a sub-graph of G. Mathematically, we want to check if there is a mapping $S(V' \mapsto V)$, s.t. $\forall(v_1, v_2) \in E', (S(v_1), S(v_2)) \in E$.

Suppose, $N = V$. For each edge $e = (v_1, v_2) \in E$, add two 2-grams (v_1v_2, v_2v_1) in the normal profile (T_N). Suppose $M = V'$. For each edge $e' = (v_1, v_2) \in E'$, we add two 2-grams (v_1v_2, v_2v_1) in the attack profile (T_M).

If the above 2-gram matching problem has a solution, then we can find a mapping $S(V' \mapsto V)$ such that for all 2-grams $(a_1a_2) \in T_M$, $S(a_1a_2) \in T_N$. Since the 2-grams in T_M correspond to edges in G' and the 2-grams in T_N correspond to edges in G, the above statement suggests that $\forall e' \in G', S(e') \in G$. This means that graph G' is isomorphic to a sub-graph of G with mapping given by S.

Also, if there does not exist a solution to the 2-gram matching problem, then there does not exists a substitution S_t such that G' is a sub-graph of G after substitution. Otherwise, S_t will result in a successful 2-gram mapping.

Thus, the 2-gram matching problem is at least as hard as the sub-graph isomorphism problem. It is known that the sub-graph isomorphism problem is NP-complete. Also, we have already proved that the 2-gram matching problem is in NP. Thus, the 2-gram matching problem is NP-complete. ∎

Even if an IDS allows constant number of mismatches, it can be shown that the problem still remains NP-complete. This is followed by the result that sub-graph isomorphism with constant number of edge insertion, deletion, and substitution is also NP-complete. This means that an attacker cannot get the substitution that will match the normal profile with a small constant number of mismatched 2-grams. Also, the one-to-one substitution problem can be easily reduced to one-to-many substitution. Thus, solving one-to-many substitution is also hard.