Evaluating the Utility of Anonymized Network Traces for Intrusion Detection

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Abstract

Recently, it has become increasingly important for computer security researchers and incident investigators to have access to larger and more diverse data sets. At the same time, trends towards protecting customer privacy have grown as a result of many embarrassing releases—of supposedly anonymous information—which has been traced back to individual computer users [7, 15]. This has further increased reluctance of data owners to release large data sets to the research community or to share logs relevant to attacks from a common threat. The burgeoning field of data sanitization has helped alleviate some of these problems as it has recently provided many new tools for anonymizing sensitive data, but there is still a difficult trade-off to be negotiated between the data owner’s need for privacy and security and the analyst’s need for high utility data. Data sanitization policies must be created that are secure enough for the first party, but do not result in too much information loss to be usable to the second.

Necessary to solving this problem of negotiating policies for data sanitization is the ability to analyze the effects of anonymization on both the security of the sanitized data and the utility left after anonymization. In this paper, we focus on analyzing the utility of network traces post-anonymization. Of course, any such measure of utility will naturally be subjective to the type of analysis being performed. So this work scopes the problem to utility for the task of attack detection. We employ a methodology we developed that analyzes the effect of anonymization on Intrusion Detection Systems (IDS), and we provide the first rigorous analysis of single field anonymization on IDS effectiveness. This work will begin to answer the questions of whether the field affects anonymization more than the algorithm; which fields have a larger impact on utility; and which anonymization algorithms have a larger impact on utility.

1 Introduction

The ability to safely share log files and network traces has become increasingly important to several communities: networking research, computer security research, incident response, and education [23]. Synthetically generated data is abundant, but has been highly criticized for many uses [14]. Honeynets can be useful in generating exercises for students and help meet the needs of educators [1], but very few honeynets have been setup on a scale to generate some of the large, cross-sectional data sets needed by computer security researchers [25]. Furthermore, using a honeynet does not necessarily release the owner from all legal responsibility when sharing data [19]. Lastly, nothing but real data will suit the needs of the incident responder who must share data about specific attacks under investigation of real machines. Therefore, there is a high demand for methods to share real log files and network traces within several communities.

At the same time as there is an increased need to share these data sets, there is increased reluctance. First, many data owners recognize the inherent security risks of releasing detailed information that could be used to map out their own networks, services or sensor locations [3, 4, 8, 10, 16, 17, 26, 28]. Secondly, there are serious privacy concerns that companies have about releasing customer data, especially in light of recent incidents where some publicly released data—believed to be anonymous—leaked information about specific
users [7, 13]. Lastly, recent research has questioned the legality of releasing much of the data as has been
done up until now [19].

The burgeoning field of data sanitization has helped address this tension by providing organizations, who
wish to share their data, with new tools to anonymize computer and network logs [4, 5, 12, 16, 18, 20, 21,
22, 22, 26, 27] However, little has been done to help users negotiate the difficult trade-off between the data
owner’s need for security and privacy, and the data analyst’s need for high quality data—what is called the
utility vs. security trade-off [20]. As anonymization is an inherently lossy process, and the data analyst wants
information as close to the original as possible, there is always this tension and a need to negotiate policies
that meet the needs of both parties.

Necessary to solving this problem of negotiating policies for data sanitization is the ability to analyze the
effects of anonymization on both the security of the sanitized data and the utility left after anonymization.
In this paper, we focus upon the latter problem of evaluating the effects of anonymization on the utility of
the data sets to be shared. Of course, utility is subjective since it depends upon who is using the data,
or more specifically, for what purpose it is being used. Hence, what is important to a researcher in the
network measurements community may be completely irrelevant to the incident responder. Therefore, we
have scoped this work to evaluating utility for attack detection.

The task of attack detection is an important part of the incident responder’s daily job. When investigating
broad attacks, of which their organization is only a part, they may have to settle for anonymized logs from the
other sites involved. It would be a similar case when using a distributed or collaborative intrusion detection
system that crosses organizational boundaries. Output from the sensors may need to be anonymized. Not
only is attack detection important in these “real world” applications, but it is important to the intrusion
detection research community, as well. This community has often complained that their only good data sets
to test new technologies against are synthetic. However, if they can still do their analysis with anonymized
data, then they are more likely to obtain large, real data sets.

The utility of a data set is not only constrained by the type of analysis being done with it but also
the type of data being shared. We have chosen to look at the effects of anonymization on one of the most
commonly shared and general types of data, the pcap formatted network trace. From this type of data,
many others can be derived (e.g., NetFlows) [2].

To quantitatively measure the ability to identify attacks in anonymized data, we developed what we call
the IDS Utility Metric. This measurement evaluates and compares the false positive and negative rates of a
baseline unanonymized data set with that of an anonymized data set. By doing this, we can automate an ob-
jective process to help us answer several questions: (1) How does anonymization of a particular field affect the
ability to detect an attack, (2) are there unique effects when certain pairs or triplets of fields are anonymized
together, and (3) how does the use of different types of anonymization algorithms affect attack identification?
In this paper, we present the results of anonymizing a portion of the 1999 MIT/Lincoln Labs DARPA data
set—by using the FLAIM framework—with over 150 separate anonymization policies to help us answer these questions.

The rest of the paper is organized as follows. Section 2 describes the anonymization algorithms used
by FLAIM in our experiments, while section 3 describes the methodology and setup of our experiments.
In section 4 we present our results and analysis. We survey the related work in section 5 and state our
conclusions, as well as scope out future work to be done, in sections 7 and 8.

2 FLAIM: Framework for Log Anonymization and Information Management

We chose to use FLAIM as our anonymization engine for several reasons. First, we could easily script
its execution for a multitude of tests. Second, it has a very flexible XML policy language that made it
simple to generate hundreds of unique anonymization policies. Third, it can anonymize as many or more
fields in PCAP traces as any other anonymization tool. Lastly, FLAIM has a very rich set of anonymization
algorithms that can be applied to all these fields. With these properties, it was the ideal tool for our
Figure 1: This diagram illustrates the process by which we compare anonymized logs versus non-anonymized logs.

2.1 Anonymization Algorithms

FLAIM implements a plethora of anonymization algorithms for several data types. The three basic data types available to most anonymization algorithms are binary, string, and numeric. Additionally, there are a few special data types like timestamps. Binary data is just treated as a string of bits with no special structure. Algorithms anonymizing binary data output binary data of the same length. String data are variable length, terminated by a null character. Anonymization algorithms that take in strings will also output strings. However, the length may change. Numeric data is interpreted as a number of a given base, specified in the anonymization policy. This is useful, for example, when working with decimal numbers like a port number. There, one may want to act on individual digits, rather than bits (e.g., replacing the last 3 digits with 0’s).

Table 10 lists the different anonymization algorithms in FLAIM along with the data types they operate upon. Further information on these algorithms can be found in [6].

2.2 Anonymization Policies in FLAIM

FLAIM provides an expressive and powerful method for specifying anonymization policies that can be modified at run time, thus enabling efficient automation. An anonymization policy is an XML file that specifies the anonymization algorithms that should be applied to the various fields in the log, along with any special parameters to be passed to those algorithms.

3 Methodology

For all of our experiments, we used a subset of the 1999 DARPA evaluation data set. The Defense Advanced Research Projects Office (DARPA) created an Intrusion Detection Evaluation testbed in 1998 and 1999. Data was captured from a simulated network that was subjected to various attacks. This data set has been frequently used in evaluating intrusion detection systems since its creation [11]. Thus, we found it appropriate to use in evaluating the effects anonymization of data can have on intrusion detection.
As we mention, we used but a portion of the 1999 data set. Specifically, we used the inside tcpdump data from Wednesday of the second week of the evaluation. Since FLAIM currently just anonymizes TCP, UDP and ICMP, we filtered out all other network protocols before running our experiments, whose methodology is depicted in Figure 1.

The **IDS Utility Metric** is constructed as follows. First, the unanonymized data set is processed by Snort to produce the “baseline” set of alerts, using the default Snort rule sets. We consider this the ideal set of alerts for the data set. Next, we take the same data set, and anonymize it—in our case, with FLAIM. We then take the anonymized data set, and we run Snort against it with the same rule set as before. The alerts generated from the unanonymized file are used as a baseline against which the alerts generated by the anonymized file are compared. The difference between the alerts in the anonymized file, versus the unanonymized file, is used as a measure of the loss of utility in the log. The larger the difference, the more information was not available in the logs in order for the IDS to correctly identify an attack. This process is depicted in Figure 1.

FLAIM schemas specify a set of anonymization algorithms that are appropriate for each field in a pcap log. These are summarized in Figure 4. In this evaluation, we only consider anonymization policies that transform single fields. Before we can evaluate the affect of multi-field policies, we must come to an understanding of single field policies. There are 152 single field policies that can be generated for pcap data (Figure 4 in the Appendix lists all the fields and anonymization algorithms used for testing). Each anonymization algorithm also has parameters that affect how it anonymizes the field. We will not go over the parameters in detail, but instead refer readers to the FLAIM manual [6]. Table 9 in the Appendix summarizes the parameter settings for the anonymization algorithms.

We iterate the process described above over each of the 152 anonymization policies, comparing the results pre- and post-anonymization. We describe how we compare these data sets in the next section, while the section after discuses the actual metric in more detail.

### 3.1 Comparing Snort Alerts

Alerts generated by Snort are defined by several properties (a full list is included in the appendix as table 8). Each alert is associated with a specific packet. The relevant alert fields—for our purposes—are listed below:

- `timestamp`: the timestamp from the offending packet.
- `sig_generator`: the part of Snort generating alert.
- `sig_id`: the Id. number of the signature that was fired.
- `msg`: description of the alert.
- `proto`: the protocol of the offending packet.
- `src`: the source IP address of the offending packet.
- `srcport`: The source port of the offending packet.
- `dst`: the destination IP address of the offending packet.
- `dstport`: the destination port of the offending packet.
- `id`: Packet Id.

To determine whether two alert sets are equal we need a way of determining if two alerts are equal. Normally this can be done by comparing each field of the alerts. However, in this case the alerts generated from the anonymized log will cause alerts that are actually equal to appear unequal. To overcome this, we compare alerts on fields which will not change due to anonymization. This leads to two distinct field sets that must be used when comparing alerts. They are shown in Table 1. Field Set 1 is used when the timestamp field has not been anonymized. Field Set 2 is used when the timestamp field has been anonymized.
Field Set 1 | Field Set 2
---|---
timestamp | sig_id
sig_id | src
id | srcport
dst | dstport
dstport | id
tcpseq

Table 1: The two field sets that are used to compare alerts.

3.2 Metrics for evaluating utility

The purpose of anonymization is to share logs while hiding sensitive information. Anonymization, while inherently an information reducing procedure, must be measured in terms of the amount of information that is lost in the file. However, by anonymizing we can introduce new false patterns into the data. The “best” anonymization policy should minimize information loss, while not adding any new false patterns to the log.

We can consider the IDS process as a pattern classification process. The data set is input, and the IDS classifies each packet as malicious or not. The alerts generated from the unanonymized data (which we call the baseline data) are considered to be the correct analysis of the data set. We then compare the alerts generated by the anonymized data to the baseline data alert set.

Let the set of alerts generated from the baseline file be called $A_{baseline}$ and the set of alerts generated from the anonymized file be called $A_{anony}$. In terms of alerts we should compare $A_{anony} vs. A_{baseline}$. The best result would be for the anonymized alerts to match, exactly, the alerts generated in the baseline set. Let us consider the baseline alerts to be the target set. The alerts from the anonymized file will be the generated set. Then we can define several metrics:

**True Positive** $TP = |A_{anony} \cap A_{baseline}|$ The number of alerts in $A_{anony}$ that are also in $A_{baseline}$.

**False Positive** $FP = |A_{anony} \setminus (A_{anony} \cap A_{baseline})|$ The number of alerts that were generated by the anonymized file, but were not in the baseline file.

**False Negative** $FN = |A_{baseline} \setminus (A_{anony} \cap A_{baseline})|$ The number of alerts that were not caught by the anonymized file.

The True Positive rate indicates how much of the information was preserved in the anonymized log. The False Positive rate indicates how many additional patterns were added to the log through anonymization. The False Negative rate indicate the amount of information that was removed from the log. A good anonymization policy should make sure both False Positive and False Negative are low while maximizing the True Positive rate.

While the false positive rate is an important factor of primary importance is the false negative rate, as it indicates the loss of information through anonymization. For the remainder of this paper, we use both False Positive and False Negative rates as a measure of the utility of a log post-anonymization, but focus more on the false negative rate.

4 Results and Analysis

In this section, we describe the results of our experiments with single field anonymization policies. These experiments provide a substantive start to answering these questions:

- What affects utility more, the fields that are anonymized or the anonymization algorithm?
- Which fields have a larger impact on the utility of a log?
• Which anonymization algorithms have a larger impact on the utility of a log?

To answer these questions, we evaluated all 152 pairs of fields and anonymization algorithms. For each pair, the number of alerts generated by Snort was calculated. The alerts generated for each pair were compared with the baseline alerts (See Table 2 and Table 3). False Positives/False Negatives were calculated based on the definitions above, whose detailed results we discuss later.

The unanonymized file produced 81 alerts. The number and types of alerts produced are summarized in Table 4. There are a total of 81 alerts generated in the baseline file, but only 19 unique types of alerts.

4.1 Fields or Anonymization Algorithms?

It is important to understand which causes a greater impact on utility; the field that is being anonymized or the anonymization algorithm that is being applied.

To evaluate the effects of anonymizing a field we calculate the marginal of a field. The marginal of a field is the average number of false positive/false negatives over all anonymization algorithms. Similarly, the marginal of an anonymization algorithm is the false positive/false negative rate averaged over all fields. The marginal provides a concise summary of the effect of anonymizing a particular field or using a particular anonymization algorithm.

Figure 2 shows the false positive and false negative marginals of the fields. The full data for these graphs is in Table 6. Figure 3 shows the false positive and false negative marginals of the anonymization algorithms. The full data for these graphs is in Table 5.

![Field Vs. Avg. False Positive Rate](image)

![Field Vs. Avg. False Negative Rate](image)

Figure 2: The left hand chart shows the marginal of each field with respect to false positives (i.e, the average number of false positives for a field, averaged over all anonymization algorithms). The right hand chart shows the marginal of each field with respect to false negatives.

The fact that the majority of fields have no impact on utility, even when anonymized in numerous ways, indicates that fields are more important than the anonymization algorithm in determining the utility of an anonymized log. If it was the other way around, we would expect false positives and false negatives to be more evenly distributed over all the fields.

Figure 2 indicates that the majority of fields generate no false positives or false negatives. The fields for which this is true (such as DST_MAC) did not affect the utility of the log under any anonymization algorithm. We can conclude that anonymizing these fields has no impact on the utility of a log, with respect to the IDS metric.

Consider the false positive rate first. We can see that very few fields generated any false positives. This indicates that anonymization, usually, does not add new patterns.
Table 2: Alerts generated for Anonymization-Field pairs. **AnonyAlg** is the anonymization algorithm used; **Field** is the field which it was applied on; **NumAlerts** is the number of alerts that were generated; **NumTypesOfAlerts** is the number of different types of alerts generated. Table 1 of 2.

| AnonyAlg              | Field          | NumAlerts | NumTypes OfAlerts |
|-----------------------|----------------|-----------|-------------------|
| BinaryBlackMarker     | SRC_MAC        | 81        | 19                |
| BytesTruncation       | SRC_MAC        | 81        | 19                |
| Annihilation          | SRC_MAC        | 81        | 19                |
| MacRandomPermutation  | SRC_MAC        | 81        | 19                |
| BinaryBlackMarker     | DST_MAC        | 81        | 19                |
| BytesTruncation       | DST_MAC        | 81        | 19                |
| Annihilation          | DST_MAC        | 81        | 19                |
| MacRandomPermutation  | DST_MAC        | 81        | 19                |
| IPv4PrefixPreserving  | IPV4_SRC_IP    | 1014      | 5                 |
| BinaryBlackMarker     | IPV4_SRC_IP    | 9         | 4                 |
| Annihilation          | IPV4_SRC_IP    | 9         | 4                 |
| RandomPermutation     | IPV4_SRC_IP    | 9         | 4                 |
| NumericTruncation     | IPV4_SRC_IP    | 9         | 4                 |
| IPv4PrefixPreserving  | IPV4_DST_IP    | 759       | 5                 |
| BinaryBlackMarker     | IPV4_DST_IP    | 9         | 4                 |
| Annihilation          | IPV4_DST_IP    | 9         | 4                 |
| RandomPermutation     | IPV4_DST_IP    | 14        | 5                 |
| NumericTruncation     | IPV4_DST_IP    | 9         | 4                 |
| BinaryBlackMarker     | IPV4_ID        | 81        | 19                |
| Annihilation          | IPV4_ID        | 81        | 19                |
| NumericTruncation     | IPV4_ID        | 81        | 19                |
| RandomPermutation     | IPV4_ID        | 81        | 19                |
| Classify              | IPV4_ID        | 81        | 19                |
| Annihilation          | IPV4_OFFSET    | 81        | 19                |
| BinaryBlackMarker     | IPV4_TTL       | 81        | 19                |
| Annihilation          | IPV4_TTL       | 81        | 19                |
| NumericTruncation     | IPV4_TTL       | 81        | 19                |
| RandomPermutation     | IPV4_TTL       | 81        | 19                |
| Classify              | IPV4_TTL       | 81        | 19                |
| Annihilation          | IPV4_CHECKSUM  | 81        | 19                |
| BinaryBlackMarker     | TCP_DST_PORT   | 520290    | 2                 |
| NumericTruncation     | TCP_DST_PORT   | 457410    | 6                 |
| Substitution          | TCP_DST_PORT   | 923033    | 2                 |
| Annihilation          | TCP_DST_PORT   | 923033    | 2                 |
| RandomPermutation     | TCP_DST_PORT   | 18        | 2                 |
| Classify              | TCP_DST_PORT   | 521670    | 2                 |
| BinaryBlackMarker     | TCP_SRC_PORT   | 380527    | 4                 |
| NumericTruncation     | TCP_SRC_PORT   | 294519    | 6                 |
Table 3: Alerts generated for Anonymization-Field pairs. **AnonyAlg** is the anonymization algorithm used; **Field** is the field which it was applied on; **NumAlerts** is the number of alerts that were generated; **NumTypesOfAlerts** is the number of different types of alerts generated. Table 2 of 2

| AnonyAlg            | Field          | NumAlerts | NumTypes OfAlerts |
|---------------------|----------------|-----------|--------------------|
| Substitution        | TCP_SRC_PORT   | 922171    | 6                  |
| Annihilation        | TCP_SRC_PORT   | 922171    | 6                  |
| RandomPermutation   | TCP_SRC_PORT   | 20        | 4                  |
| Classify            | TCP_SRC_PORT   | 381954    | 4                  |
| BinaryBlackMarker   | TCP_SEQEQUENCE | 81        | 19                 |
| NumericTruncation   | TCP_SEQEQUENCE | 65        | 15                 |
| Annihilation        | TCP_SEQEQUENCE | 65        | 15                 |
| Classify            | TCP_SEQEQUENCE | 81        | 19                 |
| BinaryBlackMarker   | TCP_ACK_NO     | 62        | 16                 |
| NumericTruncation   | TCP_ACK_NO     | 56        | 14                 |
| Annihilation        | TCP_ACK_NO     | 56        | 14                 |
| Classify            | TCP_ACK_NO     | 81        | 19                 |
| BinaryBlackMarker   | TCP_FLAGS      | 5         | 3                  |
| NumericTruncation   | TCP_FLAGS      | 5         | 3                  |
| Annihilation        | TCP_FLAGS      | 5         | 3                  |
| BinaryBlackMarker   | TCP_WINDOW     | 81        | 19                 |
| NumericTruncation   | TCP_WINDOW     | 81        | 19                 |
| Annihilation        | TCP_WINDOW     | 81        | 19                 |
| Classify            | TCP_WINDOW     | 81        | 19                 |
| Annnihilation       | TCP_CHECKSUM   | 81        | 19                 |
| BinaryBlackMarker   | TCP_UURENT     | 81        | 19                 |
| NumericTruncation   | TCP_UURENT     | 81        | 19                 |
| Annnihilation       | TCP_UURENT     | 81        | 19                 |
| Classify            | TCP_UURENT     | 81        | 19                 |
| Annnihilation       | TCP_OPTIONS    | 81        | 19                 |
| BinaryBlackMarker   | UDPU_DST_PORT  | 81        | 19                 |
| NumericTruncation   | UDPU_DST_PORT  | 81        | 19                 |
| Substitution        | UDPU_DST_PORT  | 81        | 19                 |
| Annnihilation       | UDPU_DST_PORT  | 81        | 19                 |
| RandomPermutation   | UDPU_DST_PORT  | 81        | 19                 |
| Classify            | UDPU_DST_PORT  | 81        | 19                 |
| Annnihilation       | UDPU_CHECKSUM  | 81        | 19                 |
| RandomTimeShift     | TS_SEC         | 81        | 19                 |
| TimeUnitAnnihilation| TS_SEC         | 81        | 19                 |
| Annihilation        | TS_SEC         | 81        | 19                 |
| BinaryBlackMarker   | TS_SEC         | 83        | 20                 |
| TimeEnumeration     | TS_SEC         | 399       | 19                 |
| Annnihilation       | TS_USEC        | 81        | 19                 |
Table 4: Alerts generated in the baseline unanonymized file. AlertID is the id of the alert; Num is the number of that type of alert generated; Desc is a description of the alert.

| AlertID | Num | Desc                        |
|---------|-----|-----------------------------|
| 1       | 1   | (portscan) TCP Portscan     |
| 323     | 1   | FINGER root query           |
| 330     | 1   | FINGER redirection attempt  |
| 332     | 1   | FINGER 0 query              |
| 356     | 1   | FTP passwd retrieval attempt|
| 359     | 1   | FTP satan scan              |
| 503     | 4   | MISC Source Port 20 to 1024 |
| 1200    | 9   | ATTACK-RESPONSES Invalid URL|
| 1201    | 12  | ATTACK-RESPONSES 403 Forbidden|
| 1288    | 4   | WEB-FRONTPAGE /vti_bin/ access|
| 1292    | 30  | ATTACK-RESPONSES directory listing|
| 1418    | 2   | SNMP request tcp            |
| 1420    | 2   | SNMP trap tcp               |
| 1421    | 1   | SNMP AgentX/tcp request     |
| 2467    | 1   | NETBIOS SMB D$ unicode share access|
| 2470    | 1   | NETBIOS SMB C$ unicode share access|
| 2473    | 1   | NETBIOS SMB ADMIN$ unicode share access|
| 3151    | 6   | FINGER / execution attempt  |
| 3441    | 2   | FTP PORT bounce attempt     |

Figure 3: The left hand chart shows the marginal of all the anonymization algorithms, with respect to false positives. The right hand chart shows the marginal of all anonymization algorithms with respect to false negatives.
4.2 Which fields have higher impact on utility?

As Figure 2 and Table 6 clearly show, the majority of fields do not generate false positives. The fields that do are TCP_DST_PORT, TCP_SRC_PORT, IPV4_SRC_IP, IPV4_DST_IP, TS_SEC, and TCP_ACK_NO.

We can see that several of the fields resulted in an average of 81 alerts. These fields (shown in italics in the table) had 0 error. Judging from these results, we can see that this set of fields did not affect the utility of the log as measured by the IDS metric.

TCP_DST_PORT and TCP_SRC_PORT generated the most false alerts on average. Upon inspection of the generated alert files, we can see that most of the pairs generated only 2 types of alerts. In the case of BinaryBlackMarker there were 520286 alerts of type 524. Alert 524 is “BAD-TRAFFIC tcp port 0 traffic”. The other anonymization algorithms produced the same pattern—the majority of alerts were of type 524.

The reason for this is the value we substitute for the port field. The BinaryBlackMarker, Substitution, NumericTruncation, and Annihilation algorithms all replaced the port field with 0. This resulted in the alert being triggered for nearly all the packets in the log (See Table 9 for the parameter settings of the anonymization algorithms). The same problem occurs for the TCP_SRC_PORT field.

The RandomPermutation algorithm replaced the port number with another, random port number, thus infrequently causing the generation of the BAD-TRAFFIC alert. It is clear from this that the false positive rate was greatly affected by the choice of the substitution port. However, the effect would have been less pronounced had we counted the types of new alerts rather than the raw alerts, themselves.

Arguably, it is the false negative count that is most important in determining the utility of a log. A low false negative count indicates that little information was lost in the process of anonymization. In terms of false negatives, we find that there are 8 fields that have an impact on the average false negative rate: TCP_DST_PORT, TCP_FLAGS, TCP_SRC_PORT, IPV4_DST_IP, IPV4_SRC_IP, TCP_ACK_NO, TCP_SEQUENCE, and TS_SEC.

4.3 What anonymization algorithms have higher impact on utility?

Figure 3 summarizes the false positive and false negative rates with respect to anonymization algorithm. For each anonymization algorithm, the average false positive/false negative rate is calculated over all the fields. Table 5 contains the data for the graphs.

We can see from these that most anonymization algorithms have an impact on the utility of a log. In contrast, the field data that we saw before showed strong structure in what fields affected utility. When viewed from the perspective of anonymization algorithms, there is no single anonymization algorithm that stands out.

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It might seem like the substitution algorithm has the largest effect with a huge number of alerts. However, this is because of the parameter setting used. By looking at the false negative rate we can see that while substitution still has a large effect on utility, most of the other algorithms have an effect as well.

5 Multi-Field Policy Analysis

By multi-field anonymization policies, we are referring to anonymization schemes that transform two or more fields in a log. The bulk of this work has focused on single field policy analysis. However, single field policy analysis will lay the groundwork for understanding more complex multi-field policies.

Multi-field policies are difficult to analyze because the fields are often related in subtle ways, not just very direct ways, such as between the ACK and SEQ numbers. The anonymization of additional fields certainly does not affect the total number of false positive alerts in a linear way. For example, examine Table 7.

Here, we see that anonymizing 3 fields separately produces 1014, 7 and 399 false alerts, respectively. If we anonymize the first 2 fields, we get 1016 ≠ 1014 + 7 alerts. This may not be too surprising. However, if
Table 5: False negative/positive counts for an anonymization algorithm, aggregated over all log fields.

| Anonymization Alg.         | False Negatives | False Positive |
|----------------------------|-----------------|----------------|
| Annihilation               | 10.62           | 47312.69       |
| BinaryBlackMarker          | 13.43           | 30027.37       |
| BytesTruncation            | 0               | 0              |
| Classify                   | 8.5             | 50200.83       |
| IPv4PrefixPreserving       | 28.8            | 32692.13       |
| MacRandomPermutation       | 0               | 0              |
| NumericTruncation          | 17.96           | 32692.13       |
| RandomPermutation          | 16.72           | 2.11           |
| RandomTimeShift            | 0               | 0              |
| Substitution               | 38              | 461298.5       |
| TimeEnumeration            | 1.25            | 80.75          |
| TimeUnitAnnihilation       | 0               | 0              |

Table 6: False negative/positive counts for a field, aggregated over all anonymization algorithms

| Field       | False Negatives | False Positive |
|-------------|-----------------|----------------|
| DST_MAC     | 0               | 0              |
| IPV4_CHECKSUM | 0           | 0              |
| IPV4_DST_IP | 72              | 151            |
| IPV4_ID     | 0               | 0              |
| IPV4_OFFSET | 0               | 0              |
| IPV4_SRC_IP | 72              | 201            |
| IPV4_TTL    | 0               | 0              |
| SRC_MAC     | 0               | 0              |
| TCP_ACK_NO  | 20              | 2.75           |
| TCP_CHECKSUM | 0             | 0              |
| TCP_DST_PORT| 77.67           | 557572.33      |
| TCP_FLAGS   | 76              | 0              |
| TCP_OPTIONS | 0               | 0              |
| TCP_SEQUENCE| 8               | 0              |
| TCP_SRC_PORT| 75.5            | 483554.83      |
| TCP_URGENT  | 0               | 0              |
| TCP_WINDOW  | 0               | 0              |
| TS_SEC      | 1.2             | 65.2           |
| TS_USEC     | 0               | 0              |
| UDP_CHECKSUM | 0             | 0              |
| UDP_DST_PORT| 0               | 0              |
| UDP_SRC_PORT| 0               | 0              |

Table 7: This table shows that a multi-field policy has uncertain affects on the utility of a log

| Policy                                      | Alerts |
|---------------------------------------------|--------|
| IPV4_SRC_IP-IPv4PrefixPreserving            | 1014   |
| TCP_SRC_PORT-RandomPermutation              | 7      |
| TS_SEC-TimeEnumeration                      | 399    |
| IPV4_SRC_IP,TCP_SRC_PORT                    | 1016   |
| IPV4_SRC_IP,TCP_SRC_PORT and TS_SEC         | 1010   |
we do all 3 fields together, we get only 1010 alerts—rather than something around 1420 = 1014 + 7 + 399. This is actually fewer false alerts than any one field being anonymized in isolation.

So while there is always more information loss when anonymizing more fields, there may be a critical point at which one starts getting fewer false positives as they do additional anonymization. We suspect that this is always the case since complete anonymization will leave nothing to alert upon. But clearly, more analysis must be done on multi-field anonymization, and our future work will be focused on evaluating multi-field anonymization policies.

6 Related Work

Work in data sanitization for computer and network logs to date has focused almost entirely upon development of tools [20, 9, 27, 13, 6, 17] and anonymization algorithms [26], with little to no work doing any formal analysis of the effects of anonymization. This is an important aspect missing from the research body since without it, we just have a lot of tools to haphazardly anonymize data without knowing how to do it wisely or effectively. This is also in stark contrast to k-anonymity [24] which is usually applied to medical and census type data and has received much more attention from the research community.

While writing this paper, a new piece of work closely related to ours appeared [27]. Though this is mostly a paper presenting yet another anonymization tool for pcap logs, at the end they introduce a similar method of analyzing the effects of anonymization of pcap traces by use of an IDS. Theirs is a cursory analysis, only considering anonymization of one field at a time and for only a few different fields. Also, their analysis only considered the number of alerts, where the more alerts are generated the more “security analysis” is provided. Clearly, more than just the number of alerts needs to be considered when evaluating utility, such as the false positive and negative rates. We were unable to reproduce their results (which may be because they used an unspecified subset of the LBNL data set[2]), but more troubling is the use of this data set in the first place. To evaluate the effects of anonymization, one must start with unanonymized data. However, this LBNL data set is already anonymized. So one has no clean baseline with which to compare the anonymized data in this case.

7 Conclusions

Anonymization can be a powerful tool to allow greater cooperation between organizations. The need for cooperation is strikingly clear. However, a clear understanding of the needs of the data provider and the client is necessary before flexible, effective sharing between organizations can occur.

The objective of this paper has been to begin to formally evaluate the utility vs. security trade off. The IDS metric is simple yet effective in evaluating the difference in utility when anonymizing different fields in different ways.

In this paper, we have focused on answering three questions: whether the field affects anonymization more than the algorithm; which fields have a larger impact on utility; and which anonymization algorithms have a larger impact on utility.

We have provided a thorough evaluation of single field anonymization polices upon pcap formatted network traces. We found that the primary impact on the utility of a log is not the particular anonymization algorithm, but rather the field that was anonymized.

In addition, we were able to empirically show a range of utilities for a log based on the field that was anonymized. The loss of utility was largest for ports and IP addresses. There was some loss of utility for the fields of ID, sequence number, flags, timestamp, and ACK number. However, for many of the fields there was no change in utility when anonymized.

This empirical evaluation provides the basis for further work on studying the impact of more complex anonymization schemes on the utility of a log.

\(^2\)http://www.icir.org/enterprise-tracing/
8 Future Work

There are numerous ways in which this work can be extended. First of all, it is clear that evaluating utility via Snort generated IDS alerts will cause the utility to depend upon the rule set. In fact, it is as of yet unclear exactly how the rule set impacts the utility measure. Though, we suspect there is a significant effect since we found the specific fields anonymized has more effect than how it was anonymized, and Snort rules usually focus on a one or two fields.

While we used Snort for all of our experiments, it is just one IDS and only one type. It would be very interesting to investigate whether anomaly-based IDSs are affected in similar ways.

The strength of an anonymization algorithm is a measure of how difficult it is to “break” or “de-anonymize” a log that has been anonymized via the algorithm. It is clear that we want strong anonymization algorithms so that attackers will have a difficult time to break the algorithm. As [20] points out, there is a trade off between the security of an anonymization algorithm and the utility of the log. We have not discussed the strength of an anonymization algorithm in this work.

Our work is currently limited to anonymization policies for just one field. Our next step would be to extend this work to multiple field anonymization policies and to work with more realistic data. The DARPA evaluation data set is useful because it is supervised, however it is still synthetic. In the future, we will be gaining access to other large unanonymized data sets that we can use instead of the DARPA data. However, it is important for this research to have unanonymized baseline sets.

Finally, we have still focused on utility for just one task, attack detection. An incident responder does more than just detect attacks, and in the future, we could look at how anonymizing logs affects other important security related tasks—such as alert correlation.

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9 Appendix

| Field         |
|---------------|
| timestamp     |
| sig_generator |
| sig_id        |
| sig_rev       |
| msg           |
| proto         |
| src           |
| srcport       |
| dst           |
| dstport       |
| ethsrc        |
| ethdst        |
| ethlen        |
| tcpflags      |
| tcpseq        |
| tcpack        |
| tcplen        |
| tcpwindow     |
| ttl           |
| tos           |
| id            |
| dgmlen        |
| iplen         |
| icmptype      |
| icmpcoe       |
| icmpid        |
| icmpseq       |

Table 8: Fields in a SNORT alert.
| Fields             | Anonymization                          | Fields             | Anonymization                          | Fields             | Anonymization                          |
|-------------------|----------------------------------------|-------------------|----------------------------------------|-------------------|----------------------------------------|
| SRC_MAC           | BinaryBlackMarker                      | TCP_SEQUENCE      | BinaryBlackMarker                      | ICMP_TS_ORIG      | RandomTimeShift                        |
| DST_MAC           | BytesTruncation Annihilation MacRandomPermutation | TCP_ACK_NO       | NumericTruncation Annihilation          | ICMP_TS_REC       | BinaryBlackMarker Annihilation         |
|                   |                                        | TCP_WINDOWS       |                                        | ICMP_TS_TRANS     | TimeUnitAnnihilation TimeEnumeration    |
|                   |                                        | TCP_URGENT        |                                        | TS_SEC            |                                        |
| IPV4_DST_IP       | IPv4PrefixPreserving                   | TCP_FLAGS         | BinaryBlackMarker                      | IPV4_OFFSET       | Annihilation                           |
| IPV4_SRC_IP       |                                        |                   | NumericTruncation Annihilation          | IPV4_CHECKSUM     |                                        |
| ICMP_IPV4_SRC_IP  | IPv4PrefixPreserving                   | ICMP_GATEWAY      | IPv4PrefixPreserving                   | TCP_CHECKSUM      |                                        |
| ICMP_IPV4_DST_IP  |                                        |                   | BinaryBlackMarker                      | TCP_OPTIONS       |                                        |
| IPV4_ID           | BinaryBlackMarker                      | ICMP_IPV4_LENGTH  | NumericTruncation Classify             | UDP_CHECKSUM      |                                        |
| IPV4_TTL          | BytesTruncation Annihilation           |                  |                                        | ICMP_IPV4_OFFSET  |                                        |
| ICMP_TYPE         | Annihilation RandomPermutation         | ICMP_IPV4_IDENTIF |                                      | ICMP_IPV4_CHECKSUM|                                        |
| ICMP_IDENTIFIER   |                                       | ICMP_IPV4_SEQ     |                                        | TS_USEC           |                                        |
| ICMP_POINTER      | BinaryBlackMarker                      | ICMP_IPV4_TTL     |                                        |                   |                                        |
| ICMP_IPV4_ID      | NumericTruncation Classify             | ICMP_IPV4_TTL     |                                        |                   |                                        |
| ICMP_IPV4_TTL     |                                        | ICMP_IPV4_ID      |                                        |                   |                                        |
| ICMP_IPV4_LENGTH  |                                        | ICMP_IPV4_TTL     |                                        |                   |                                        |
| ICMP_ORIG_DATA    | BinaryBlackMarker                      | TCP_DST_PORT      | Substitution                            | IPV4_LENGTH       | NONE                                    |
|                   | Annihilation                            | TCP_SRC_PORT      | BinaryBlackMarker                      | TCP_OFFSET        |                                        |
|                   |                                        | UDP_DST_PORT      | Annihilation RandomPermutation          | UDP_LENGTH        |                                        |
|                   |                                        | UDP_SRC_PORT      | NumericTruncation Classify             | ICMP_IPV4_LENGTH  |                                        |

Figure 4: PCAP Fields and Anonymization Algorithms. Each section contains the fields (on the left) on which any of the anonymization algorithms on the right can be applied. For instance, Only the anonymization algorithms BinaryBlackMarker and Annihilation can be applied to the ICMP_ORIG_DATA field (the bottom left section)
| Anonymization Algorithm     | Parameters | Description |
|-----------------------------|------------|-------------|
| IPV4PrefixPreserving        | Passphrase: foobar | Sets the anonymization passphrase. |
| MacRandomPermutation        | None       | No Parameters. |
| RandomTimeShift             | lowerTimeShiftLimit: 16250000, upperTimeShiftLimit: 31500000 | Shift time by a random amount between the lower and upper limits. |
| TimeUnitAnnihilation        | timeField: years | Annihilate the years portion of the timestamp. |
| NumericTruncation           | numShift: 5, radix: 2 | Shorten the field by 5 bits. |
| TimeEnumeration             | baseTime: 0, intervalSize: 1 | Set the time of the oldest record to 0. One timestamp is equal to adding 1 to the timestamp field. |
| RandomPermutation           | None       | No Parameters. |
| Annihilation                | None       | No Parameters. |
| Classify                    | configString: 1024:0,65536:65535 | Set elements less than 1024 to 0, and all others to 65535. |
| BinaryBlackMarker           | numMarks: 8, replacement: 0 | Mark 8 bits as 0 |
| BytesTruncation             | numbits: 20, direction: left | Remove 20 bits, starting from the left. |
| Substitution                | substitute: 0 | Substitute field with 0. |
| Anonymization Alg.       | Data Type(s) | Description                                                                 |
|--------------------------|--------------|-----------------------------------------------------------------------------|
| Prefix-preserving        | binary       | Implements prefix-preserving permutation described in [26]                  |
| Truncation               | binary       | Removes suffix or prefix of data by specified number of units.             |
| Hash                     | binary       | Outputs cryptographic hash of data.                                        |
| Black Marker             | binary       | Overwrites specified number of units with specified constant.              |
| Time Unit Annihilation   | timestamp    | Annihilates particular time units (e.g., hour and minute units).           |
| Random Time Shift        | timestamp    | Randomly shifts timestamps within given window by same amount.             |
| Enumeration              | timestamp    | Preserves order, but not distance between elements.                        |
| Random Permutation       | binary       | Creates random 1-to-1 mapping.                                             |
| Annihilation             | binary       | Replaces field with NULL value.                                            |
| Classify                 | numeric      | Partitions data into multiple non-overlapping subsets.                     |
| Substitution             | binary       | Replaces all instances with a particular constant value.                   |

Table 10: Anonymization algorithms with applicable data types.