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A Streaming Statistical Algorithm for Detection of SSH Keystroke Packets in TCP Connections

Saptarshi Guha
Purdue University, West Lafayette IN 47904, USA, sguha@purdue.edu

Paul Kidwell
Lawrence Livermore Laboratories, Livermore CA 94551, USA, kidwellpaul@gmail.com

Ashrith Barthur, William S. Cleveland
Purdue University, West Lafayette IN 47904, USA, {abarthur@purdue.edu, wsc@purdue.edu}

John Gerth
Stanford University, Palo Alto CA 94305, USA, gerth@graphics.stanford.edu

Carter Bullard
QoSient LLC, carter@qosient.com

Abstract A streaming statistical algorithm detects SSH client keystroke packets in a TCP connection on any port. Input data are timestamps and TCP-IP header fields of packets in both directions, measured at a monitor on the path between the hosts. No packet content is included. The algorithm uses the packet dynamics just preceding and following a client packet with data to classify the packet as a keystroke or non-keystroke. The dynamics are described by classification variables derived from the arrival timestamps and the packet data sizes, sequence numbers, acknowledgement numbers, and flags. The algorithm succeeds because a keystroke creates an identifiable dynamical pattern. Final testing of the algorithm is based on analysis of about 1 million connections covering all common network protocols. Data visualization and the statistical design of experiments play a critical role in the analysis. It is common to treat the choice of tuning parameters of a statistical or machine learning algorithm as an optimization that finds one set of parameter values. Instead, we run a designed experiment that treats the tuning parameters as statistical tuning factors, which yields valuable information about algorithm performance. One application of the algorithm is identification of any TCP connection as an SSH interactive session, allowing detection of backdoor SSH servers. More generally, the algorithm demonstrates the potential for the use of detailed packet dynamics to classify connections, important for network security. The algorithm ~~is~~ has been implemented in the widely-used Argus traffic audit software system.

Keywords Network security, statistics, interactive SSH session, Argus network traffic auditor, backdoor login, design of experiments, data visualization

1. Introduction

The Secure Shell (SSH) protocol[16] is a widely-used, encrypted, method for Internet communication. Initially developed to replace the unencrypted Telnet protocol, SSH provides not only interactive command-line access, but also file transfer via SCP and SFTP and a general tunneling mechanism which can be used to forward arbitrary application traffic such as X11. Because of its popularity, SSH servers, which usually run on port 22, are subject to intense attacks to gain SSH login authorization. In addition, an intruder who has gained entry by any intrusion mechanism, can establish a backdoor SSH server on a nonstandard port to facilitate communication. Although any intrusion is worrisome, a human attacker who can establish an interactive SSH connection to explore a compromised machine is particularly dangerous. Such an intrusion indicates a specific interest in employing the victim machine, or seeing the information on it, or attacking the performance of applications of normal users; this is typically considered to be an emergency that warrants an urgent investigation.

For a TCP connection on any port, our streaming statistical algorithm classifies each client packet with data as an SSH keystroke packet or not. This has a number of potential applications, including classifying the connection as an interactive SSH login if SSH keystroke packets are detected. The classification variables used in the algorithm are the following:

- the arrival order number of each packet of the connection at the monitor, a positive integer
- whether a packet is from the client or server
- whether there are more than 22 packets in the connection
- whether there are client packets after packet 22 or not
- data size for client packets
- data size for server packets
- the number of packets between a client packet with data and the next acknowledging server packet with data
- interarrival time of two successive client packets with data
- interarrival time of two successive echoing server packets
- the ratio of a client interarrival time and the interarrival time of the corresponding echoing server packets
- the number of packets between two successive client packets with data.

These variables constitute a description of the detailed *packet dynamics* of a TCP connection. There exists a large body of literature devoted to the study of packet dynamics in relation to TCP performance and control e.g., [12, 13]. Our variables have some overlap with those of the TCP studies, but are not the same since our goal is network security.

Other work in network security has employed variables that also overlap with ours to detect interactive TCP logins. This past work, discussed in Section 7, uses aggregate statistics across a connection based on certain variables, and not the detailed packet dynamics of our algorithm. Our work uses the detailed dynamics because a keystroke creates a distinctive dynamical pattern, which leads to highly accurate classification. Such success has already been hypothesized by Donoho et al. [5]:

> There are also other sources of information that we haven't discussed, the key one being the two-way nature of interactive sessions. There is far more information than just the keystrokes on the forward path through the stepping stones, there are also the echoes and command output on the reverse path, and it should be possible to use information about these to substantially improve detection.

This hypothesis is not recent. Progress has been slow on the idea because study of packet dynamics for network security requires detailed, comprehensive statistical analysis of large, complex packet-level databases; just passing over the data of each connection and creating a small number of statistical summaries of each does not shed sufficient light on the dynamics. Recently, though there have been major advances in computational environments for analysis of large, complex datasets, and our work has made use of them [7].

It might be thought that aggregate statistics would scale much more readily because the packet dynamics require more detail, at least formally. In fact, working at the packet level has allowed us to develop an algorithm that is streaming and easy to implement in a traffic monitor, allowing it to scale to high traffic rates. The algorithm has been implemented in the widely-used Argus traffic audit software system, and the expectation is that it will be very efficient at high traffic rates.

The following is a guide to the article. Section 2 gives a detailed description of the streaming statistical algorithm. Section **??** describes the two-phase process of developing the algorithm from the TCP packet traces collected. The algorithm has 8 statistical tuning factors whose values have a large impact on performance; the factors are thresholds for variables used in the algorithm for keystroke detection. Section 4 describes the formal test regimens and data. Section 5 describes a designed experiment that varies the tuning factors to determine their impact on false positives and false negatives in classifying a TCP connection as interactive or non-interactive. Section 6 investigates the accuracy of classifying a client packet as a keystroke or not, using 36 scripted SSH connections. Section 7 presents past work in connection classification and the relationship to the work here. Section 8 discusses justification, results, limitations, and future work.

2. Details of the Algorithm

The algorithm consists of a sequence of 10 rules, applied in the order described below. The first two are SSH-Protocol Rules, Rules I and II, and the next 8 are Packet-Dynamics Rules, Rules 1 to 8.

A keystroke is defined as a key depression that is part of typing to create text, including the `Enter/Return` that ends the line. The definition excludes key depressions that result in navigation through a document being viewed. Key depressions that are part of the SSH handshake are not considered as keystrokes to be detected by the algorithm because their packet dynamics are quite different.

2.1. SSH-Protocol Rules

These rules are based on the specifications of the SSH protocol and not the statistical behavior of the classification variables.

Rule I. SSH Handshake Startup Deletion. Absence of Client Packets with Data. *Action: Packets with arrival order 1 to 22 are deleted. The ensuing algorithm starts at packet 23. If there are fewer than 22 packets, or if there are 23 or more but but none are client packets with data, then the the number of keystrokes in the connection is taken to be zero and the algorithm ends.*

The SSH handshake has keystrokes, for example, typing a password. However, the resulting packet dynamics are very different from those of keystrokes after an SSH interactive session is established. Furthermore, the handshake occurs for non-interactive SSH connections, which are not a target for the important application of classifying a connection as interactive SSH or not. So we do not take keystrokes of the handshake to be a target of the keystroke classification, and if a handshake positive occurs, it is considered a false positive. However, false negatives are important as well; we do not want to remove packets that are not a part of the handshake. The SSH protocol suggests that the minimum number of packets that can occur in the handshake is 22, so we take 22 as the cutoff.

It is quite unlikely that a client packet with data in the handshake would be classified as a keystroke. However, small issues such as this loom large because we seek exceptionally small error rates, for example, on the order of a few 10s per million for the application of connection classification as interactive or not.

Rule II. SSH Packet Size. *Action: Packets with arrival orders 23 and above that have data, both server and client packets, must have data sizes equal to $4k$ where k is a positive integer. If the data in any packet is not one of these sizes, then all client data packets are classified as non-keystrokes and the algorithm ends.*

The SSH protocol specifies that the data in any packet of an SSH connection, interactive or non-interactive, have the above sizes. [17].

2.2. Packet-Dynamics Rules

For connections that pass Rules I and II, each client packet with data and with packet order 23 or above is a candidate keystroke. The packet-dynamics rules classify the candidates in order of their arrival, each starting out as a keystroke candidate. If a candidate does not pass a rule, it is classified as a non-keystroke and its candidacy ends. In other words, to be classified as a keystroke, the candidate must pass Rules 1 to 8. There are 8 statistical tuning factors that provide classification limits for 8 classification variables. The conceptual framework is that keystroke packets have a greater probability to lie within the limits than non-keystroke packets. The values of the limits are chosen based on the statistical properties of the classification variables and the statistical performance of the algorithm.

Rule 1. Minimum Client Data Size. *Classification variable d_c = size of data in client packet. Statistical tuning factor $d_c^{(m)}$. Action: Candidate passes if $d_c \geq d_c^{(m)}$.*

Even though the current candidate data size d_c conforms to the SSH sizes of Rule II, there is a much smaller range of likely values of d_c for keystrokes. $d_c^{(m)}$ is a statistical tuning factor that specifies the minimum value of the likely range of d_c.

Rule 2. Maximum Client Data Size. *Statistical tuning factor $d_c^{(M)}$. Action: Candidate passes if $d_c \leq d_c^{(M)}$.*

$d_c^{(M)}$ is a statistical tuning factor that specifies the maximum value of the likely range of d_c for keystrokes.

Rule 3. Maximum Server Echo Gap Size. *Classification variable g_s = server echo gap count. Statistical tuning factor $g_s^{(M)}$. Action: candidate passes if $g_s \leq g_s^{(M)}$.*

The server echo packet of the current candidate packet is determined by matching the sequence number of the latter with the acknowledgement number of the former. The number of packets between the current candidate packet and its server echo is the echo gap size, g_s. It is equal to the following: (arrival order number of the echo packet) − (arrival order number of the candidate) −1. For a keystroke, the gap is not large. The maximum, $g_s^{(M)}$, is a statistical tuning factor for the maximum of the likely range of g_s for keystrokes.

Rule 4. Minimum Server Echo Data Size. *Classification variable d_s = size of data in server echo packet. Statistical tuning factor $d_s^{(m)}$. Action: candidate passes if $d_s > d_s^{(m)}$.*

As with d_c, the server echo data size d_s has a likely range of observed values for keystrokes. $d_s^{(m)}$ is a statistical tuning factor that specifies the minimum value of the likely range of d_s.

Rule 5. Maximum Server Echo Data Size. *Statistical tuning factor $d_s^{(M)}$ Action: candidate passes if $d_s \leq d_s^{(M)}$.*

$d_s^{(M)}$ is a statistical tuning factor that specifies the maximum value of the likely range of d_s for keystrokes.

Rule 6. Minimum Client Candidate Interarrival Time. *Classification variable i_s = interarrival time between the candidate packet and the last packet before the candidate that passed Rule 5. Statistical tuning factor $i_c^{(m)}$. Action: Candidate passes if $i_c \geq i_c^{(m)}$. If the current candidate packet is the first of the connection with $d_c > 0$, then it automatically passes.*

Client keystroke packets created by typing in an interactive SSH connection have cadences that speed up and slow down. There are typing bursts, short cognitive pauses, and long cognitive pauses. Thus, i_c can vary substantially for true keystrokes. However, it has a lower bound determined by the limit of human typing speed. The statistical tuning factor $i_c^{(m)}$ is a minimum for the the likely interarrival time for human typing.

Rule 7. Maximum Absolute Log Interarrival Ratio. *Variable i_s = the interarrival time between the two server echos for the two client candidates in Rule 6. Classification variable $\ell_{cs} = |\log_{10}(i_c/i_s)|$. Statistical tuning factor $\ell_{cs}^{(M)}$. Action: Candidate passes if $\ell_{cs} \leq \ell_{cs}^{(M)}$. If the current candidate packet is the first of the connection with $d_c > 0$, then it automatically passes.*

Under the assumption that congestion between the hosts is not substantial, the ratio of i_c and i_s can be expected to be close to 1 whatever the absolute value of i_c. The statistical tuning factor $|\log_{10}(i_c/i_s)|$ places a limit on the likely deviation from 1 for keystrokes.

Rule 8. Maximum Previous-Current Gap. *Classification variable g_{pc} = the previous-current gap, the count of packets between the previous and current candidates. Statistical tuning factor $g_{pc}^{(M)}$. The current candidate can pass this rule from the initial evaluation, making it a keystroke positive, or it can be deferred, making it a tentative candidate until the next candidate packet has its initial evaluation. In either case the current candidate will become the previous candidate when a new current candidate is encountered. The following actions are based on the state of the previous candidate and value of g_{pc}:*

(1) State: $g_{pc} > g_{pc}^{(M)}$, previous = tentative.
Action: previous fails; current becomes tentative.
(2) State: $g_{pc} > g_{pc}^{(M)}$, previous = passed.
Action: current becomes tentative.
(3) State: $g_{pc} \leq g_{pc}^{(M)}$, previous = tentative.
Action: previous passes; current passes.
(4) State: $g_{pc} \leq g_{pc}^{(M)}$, previous = passed.
Action: current passes.

The rule is based on behaviors during an interactive session. The typical pattern is an alternation between typing episodes at the client with each resulting in commands to the server, and output episodes from the server to the client. During a typing episode, a common transmission pattern seen by the monitor is a keystroke from the client, an echo from the server, an ACK from the client, and then the next keystroke. If this pattern occurs between the previous and current candidates, then $g_{pc} = 2$. $g_{pc}^{(M)}$ is a statistical tuning factor that is the maximum of the likely range of values of gaps between the keystrokes of a typing episode. The output of a server episode tends to create more packets, which delineates the episodes. A typing episode must have at least one letter, which results in two keystroke packets, the letter plus `Enter/Return`. (Recall that a keystroke is defined as a key depression that is part of typing to create text, including the `Enter/Return` that ends the line.) Rule 8 eliminates cases of isolated single candidate packets that are insufficiently close to other packets classified as keystrokes to be part of a typing episode, but do not have the requisite two keystrokes to be an episode.

3. Packet Trace Collection and Algorithm Development

3.1. Packet Trace Collection

Our research required packet traces — arrival timestamps and TCP/IP headers — on a gateway link carrying both directions of traffic between an inside network and the outside. The requirement corresponds to the targeted initial application of our keystroke algorithm, which is protection of an inside network by a monitor on the gateway link.

Furthermore, the research required trace collections for two types of connections: *commodity* and *scripted*. The former are the everyday traffic on a link carrying out the many applications running on the inside network. The latter are interactive connections initiated specifically for development and testing of the algorithm; they consist of prescribed commands and prescribed text input to programs that create or display documents. The commodity connections enable testing the classification of connections as interactive or non-interactive. The scripted connections enable testing of both the classification of connections, and the classification of client packets with data as keystroke or non-keystroke.

Our work started using previously collected traces of commodity connections for 4 days 18 hours from the University of Leipzig Internet access link [14]. The inside network in this case is the University of Leipzig campus and certain off-campus subnets.

The research also needed trace collection for an inside network for which we could access log files for SSH to allow us to have highly accurate determinations of whether a port 22 connection was interactive or non-interactive. We set up trace collection on a subnet of the Purdue Statistics Department. A monitor collected traces with `tcpdump` running on a server connected to the span port of a switch that sees all traffic in and out of the subnet and between two virtual LANS making up the subnet. Both commodity and scripted connections were collected. For connections with inside host port 22 we were able to access log files. But logging for the OpenSSH 5.3 server `sshd` was inadequate for verifying the correct classification, so simple modifications were made to the source code to emit additional messages for each connection. These messages captured the details of authentication and session characteristics, such as whether it was a login, single command, or subsystem request; had an allocated pseudo-tty; had requested port forwarding or X-window tunneling. Additional log messages recorded the intra-session forwarding and tunneling activity and, at session close, summary statistics on data transfer. This additional logging permits independent determination of SSH session attributes. In particular, it enabled highly accurate determinations of whether a connection with inside host port 22 was interactive or non-interactive.

We ran scripted connections at inside host port 22 that were measured by the Purdue trace collection. The `ssh` client program was modified to emit a tracer UDP packet every time it sent a keystroke packet. These tracer packets were collected by the subnet monitor along with packets from the SSH session, yielding a stream where the locations of keystroke packets for scripted connections were precisely known.

3.2. Algorithm Development

Our development of the keystroke classification algorithm was done together with study of its application to the classification of a connection as interactive or non-interactive.

The first phase of the work was an exploratory, unstructured study of traffic using both visualization methods and numeric methods of statistical analysis to gain a basic understanding of connection packet dynamics: arrival times, packet sizes, flags, sequence numbers, and acknowledgement numbers, as well as secondary variables derived from these primary variables. There was a comparison of the dynamics when keystrokes occurred and when they did not using commodity traces from Leipzig together with commodity and scripted connections from Purdue. Conclusions from this empirical study, guided by descriptions of the SSH Architecture[16] and of Transport[17] Protocols, led to a succession of algorithm versions ending in the streaming statistical algorithm described in Section 2. Details of this first phase work are not conveyed here.

The second phase of the work was formal testing to verify the algorithm specifications of the first phase, and to select the tuning factors of the algorithm. This used commodity and scripted connections from Purdue, and is described in Sections 4-6.

4. Formal Test Regimens

The streaming statistical algorithm has 8 tuning factors for Rules 1 to 8 whose values must be chosen. We studied the effects of the factors by formal test regimens. We collected or created a large number of test connections on the Purdue subnet (see Section 3). The connections were broken into 4 subsets; each had a test regimen resulting in Regimens 1 to 4. There were two types of analyses of data from the regimens. In the first, described in

Section 5, we studied the classification of the connections of Regimens 1 to 4 as interactive or non-interactive. In the second, described in Section 6, we studied the classification of candidate packets as keystrokes or non-keystrokes; just Test Regimen 1 was used for this.

4.1. Classification of Connections as Interactive or Non-Interactive

We ran a designed experiment with 243 combinations of the values of the tuning factors. This means we ran the algorithm 243 times on each test connection from Regimens 1 to 4. The response for each regimen has 243 values; each is a number of false positives or false negatives, one per combination of the factors in the experiment. The term "positive" refers to a connection that is interactive, and "negative" refers to a connection that is non-interactive. The analysis of the 4 responses reveals the effects of the factors and leads to combinations of the values of the factors that have low rates of false classification.

Test Regimen 1 used scripted interactive connections run on the Purdue subnet. They consisted of 12 precisely defined interactive scripts. They ranged from the simple command `ls` to more complex activities that used the `emacs` editor or that utilized sequences of commands. Section 6 gives more detail about the scripts. Each script, when run once, results in one SSH interactive connection. Each script was run 3 times, which resulted in 36 connections. The response variable for Test Regimen 1, `fn.22script`, takes 243 values: the numbers of false negatives out of 36 for the 243 combinations of the tuning factors.

Test Regiments 2 to 4 use Purdue subnet commodity connections. We collected five days of traffic on the subnet monitor, which resulted in 1,021,336 connections.

Of the 7964 commodity connections which had one host using port 22, Rule I eliminated the 6672 with fewer than 23 packets. Of those, 207 connections with no client data packets were dropped. Rule II, which checks conformance of packet sizes with the SSH protocol, eliminated another 38. Of these we were able to resolve all but one as actual packet errors leading to session termination. The result was 1047 connections. We were unable to deploy the revised `sshd` on all inside hosts, which reduced the 1047 commodity port 22 connections to 369 for which we could verify whether they were interactive or not. 195 are interactive and 174 are non-interactive.

Of the 1,013,372 commodity connections which did not involve port 22, Rule I eliminated 703,353 with fewer than 23 packets leaving 310,019 connections which were all assumed to be non-interactive for purposes of the test. Of those, 150,228 connections with no client data packets after packet 22 were dropped. Application of Rule II dropped another 158,516 connections, leaving 1275 connections.

Test Regimen 2 uses the 195 interactive connections of port 22. The response variable, `fn.22script`, is the numbers of false negatives out of 195 for the 243 combinations of the tuning factors. Test Regimen 3 uses the the 174 non-interactive connections of port 22. The response variable, `fp.22script`, is the numbers of false positives out of 195. Test Regimen 4 uses the 1275 connections not using port 22. The response variable, `fn.22script`, is the numbers of false positives out of 1275.

4.2. Classification of Candidate Packets as Keystroke of Non-Keystroke

The measurement mechanism for Test Regimen 1 provides knowledge of which candidate client packets in each connection are keystrokes and which are non-keystrokes. We studied false positives and false negatives for the classification of candidate packets as keystroke or non-keystroke. We did this for the 36 script connections with a single combination of values of the tuning factors that resulted in very low false positives and false negatives in the above connection classification.

TABLE 1. Statistical tuning factors and their values in the designed experiment.

Tuning Factor	Notation	Units	1	2	3
Minimum Client Data Size	$d_c^{(m)}$	bytes	48	32	24
Maximum Client Data Size	$d_c^{(M)}$	bytes	64	128	256
Server Echo Gap Size	$g_s^{(M)}$	number	2	3	4
Minimum Server Echo Data Size	$d_s^{(m)}$	bytes	44	32	24
Maximum Server Echo Data Size	$d_s^{(M)}$	bytes	64	128	256
Minimum Client Candidate Interarrival	$i_c^{(m)}$	$\log_{10}$ sec	-0.7	-1	-1.3
Maximum Absolute Log Interarrival Ratio	$\ell_{cs}^{(M)}$	$\lvert\log_{10}\text{ratio}\rvert$	0.05	0.075	0.1
Maximum Previous-Current Gap	$g_{pc}^{(M)}$	number	2	4	7

Note. Increasing candidate packet pass-through: ⟶

5. A Multi-Factor Designed Experiment

The Packet-Dynamics Rules have 8 statistical tuning factors, as described in Section 2, that are thresholds for the variables used in the rules. The factors, their mathematical notation, and their units of measurement are shown in the first 3 columns of Table 1. Performance of the algorithm is measured by the 4 responses — `fp.not22`, `fp.22`, `fn.22`, and `fn.22script` — described in Section 4. We ran a multi-response designed experiment to determine the dependence of the responses on the levels of the statistical tuning factors.

Our first-phase exploratory studies of algorithm development and performance provided insight about ranges of the factors for which the performance is reasonable. Based on this we designed and ran a multiple-response fractional-factorial statistical experiment that varied all 8 factors in a systematic way in a region deemed to have reasonable performance, and studied how the above 4 responses changed with the values of the factors.

The experiment used the 1680 connections remaining after application of the SSH-Protocol Rules to the total 1,021,336 connections, and after a small number of connections were removed for other reasons. This is described in Section 4. For Test Regimens 1 to 4, the remaining numbers are 36, 195, 174, and 1275 connections, respectively. While only 0.16% of the connections remain, an absolute number of 1680 would be far too many for security analysts to review, making the Packet-Dynamics Rules critical. These rules were applied to just the first 1500 packets of each of the 1680 connections.

The choice of tuning parameters for statistical models and algorithms is often approached in the statistics and machine learning literature as just an optimization: the best choice of the values of the tuning parameters for the responses. Running a designed experiment goes well beyond this by providing valuable knowledge about the impact of the factors on the responses, the relationship of the responses as the factors change, the sensitivity of the algorithm to the changes in the values of the factors chosen for the experiment, and the trade-off between false positives and false negatives.

5.1. Experimental Design

The first step in the design was to select 3 values of each statistical tuning factor, which are shown in the last 3 columns of Table 1. For each factor, candidate packet pass-through values increase from left to right; that is, as the factor changes left to right, more packets pass the rule test. The factors that are minima, shown with superscript m, allow more candidate packets to pass as their values decrease; their values are ordered largest to smallest. The factors that are maxima, shown with superscript M, allow more candidate packets to pass through as their values increase; their values are ordered smallest to largest.

Given 8 statistical tuning factors, there are $3^8 = 6561$ possible combinations, each requiring one experimental run. A run means applying the algorithm to each of the 1680 connections with one combination of tuning factors, and computing the values of the responses.

We chose a fractional factorial design with 243 runs from [15]. It is a minimum-aberration resolution V design that spreads the points across the 8 dimensional space of the statistical tuning factors to enable good characterization of the effects of the factors on the responses. The design has a certain balance of the values of the factors. Each of the 3 values of a factor occurs in 81 runs (81×3 = 243). Each of the 9 combinations of values of 2 factors occur 27 times (27×9 = 243).

5.2. Experimental Results: Dependencies Among the Responses

Each run of the experiment produces a 4-tuple of values of the four response variables. So the 243 runs produce 243 points in a 4-dimensional space. Figure 1 is a scatterplot matrix: all pairwise scatterplots of the four variables. Each panel has 243 points plotted. The response names appear in a diagonal of the matrix. The vertical scales of the 4 scatterplots in each row of the matrix are the variable whose name appears in the row. The horizontal scales of the 4 scatterplots in a column of the matrix are the variable whose name appears in the column. Points have been jittered, a small amount of noise added, because a number of plotting locations have multiple points. The notation for the scatterplot in column i and row j is scatterplot ij. So the lower left scatterplot is 11. Note that scatterplot ij has the same variables as scatterplot ji, but with the scales reversed.

Figure 1 reveals important relationships among the responses. Scatterplot 32 shows a substantial trade-off between `fn.22` and `fp.22`, a strong negative dependence. The same negative dependence occurs for `fn.22` and `fp.not22`. in scatterplot 31. Scatterplot 21 shows `fp.22` and `fp.not22` have a positive dependence although there are there are a number of quite low values of `fp.not22` with very large values of `fp.22`. This likely occurs because non-interactive connections at port 22, since they are SSH, can behave differently from the non-interactive connections at other ports.

We can also see that `fn.22script` is always 0. None of the 36 connections is ever classified as non-interactive across the 243 runs. This might be occurring because of conservative, slower typing in the scripts to avoid typing errors. It does suggest a certain robustness of the algorithm to different modes of typing.

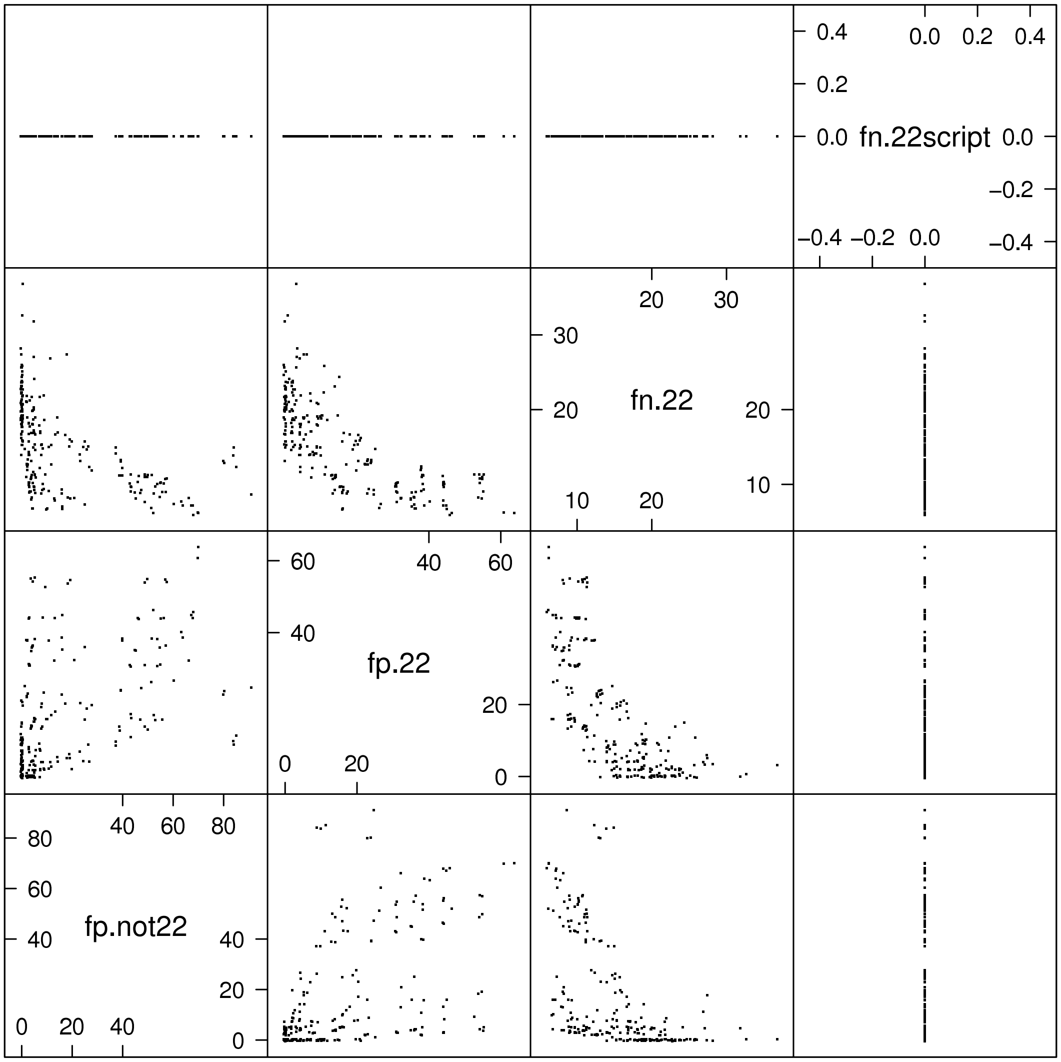
5.3. Pass-Through Analysis of False-Positives and False-Negatives

The trade-off between false positives and false negatives results from different levels of candidate packet pass-through. As discussed earlier, as we go left to right in Table 1 through the values of each statistical tuning factor, the number of candidate packets that pass the rule tends to increase. This, in principle, increases the number of false positives and decreases the number of false negatives. We can use this notion to determine the rules whose changing levels are most responsible for the trade-off.

We define a pass-through level variable for the values of the statistical tuning factors: level 1 = the lowest level (column 4 in Table 1), level 2 = the middle level (column 5), and level 3 = the highest level (column 6). Next we select two sets of runs, the good-negative set, for which `fn.22` ≤ 10, and the good-positive set, for which `fp.22` ≤ 2. The cut-off values were chosen to achieve two goals. The first, which we can see achieved in Figure 1, is that the two sets have different runs, that is, different combinations of the statistical tuning factors. The second is that the two sets have about the same number of runs; there are 66 in the good-negative and 63 in the good-positive.

Figure 2 compares the fractions of occurrence of pass-through levels 1, 2, and 3 for the two sets. There is little to negligible difference between the good-negative and good-positive sets for Rules 1, 3, 4, and 7; these rules play, overall, little role in the trade-off between false positives and false negatives. The other rules do substantially more. The fractions for the good-negative set tend to be higher for levels 2 and 3, and lower for level 1, than the good-positive set, creating more pass-through. The most dramatic differences are in Rules 2 and 5; pass-through level 1 is never taken by the good-negative runs.

FIGURE 1. Scatterplot matrix of the 4 responses — `fp.22`, `fn.22`, `fp.not22`, and `fn.22script` — for the 243 runs of the fractional factorial designed experiment.



5.4. Tuning Parameter Values for Small Values of the Responses

Trade-off of false positives and false negatives is also informative because the tolerance for each type of error is not necessarily the same for different inside networks. For the Purdue subnet, we seek false negatives as low as possible; a missed intrusion can have major consequences. False positives can be more readily tolerated provided they do not become more than a minor burden for security analysts. With this in mind, we select runs with a compromise that gives somewhat higher priority to control of false negatives: `fn.22` ≤ 10, `fp.not22` ≤ 10, `fp.22` $<= 20$, and `fn.22script` $= 0$. This was achieved by 8 runs.

Figure 3 displays the fraction of occurrences of the pass-through variable for the 8 runs in the same manner as Figure 2. Comparison of the two figures shows that for the compromise runs in Figure 3, there is a greater balancing of pass-through than in Figure 2. For Rule 8, level 1 is always the value. This means that the rule is has a tight limit of 2 packets between two keystrokes in a typing episode. For Rule 2, level 2 is always the value. This means that the rule limits the data in a client keystroke to a maximum of 128 bytes; this results from the encryption algorithms employed by SSH. For Rule 1, however, the level is not critical,

Figure 2. For each rule, the fraction of occurrences of 3 levels of the pass-through variable for a set of runs with low `fn.22` (○) and another set of runs with low `fp.22` (+).

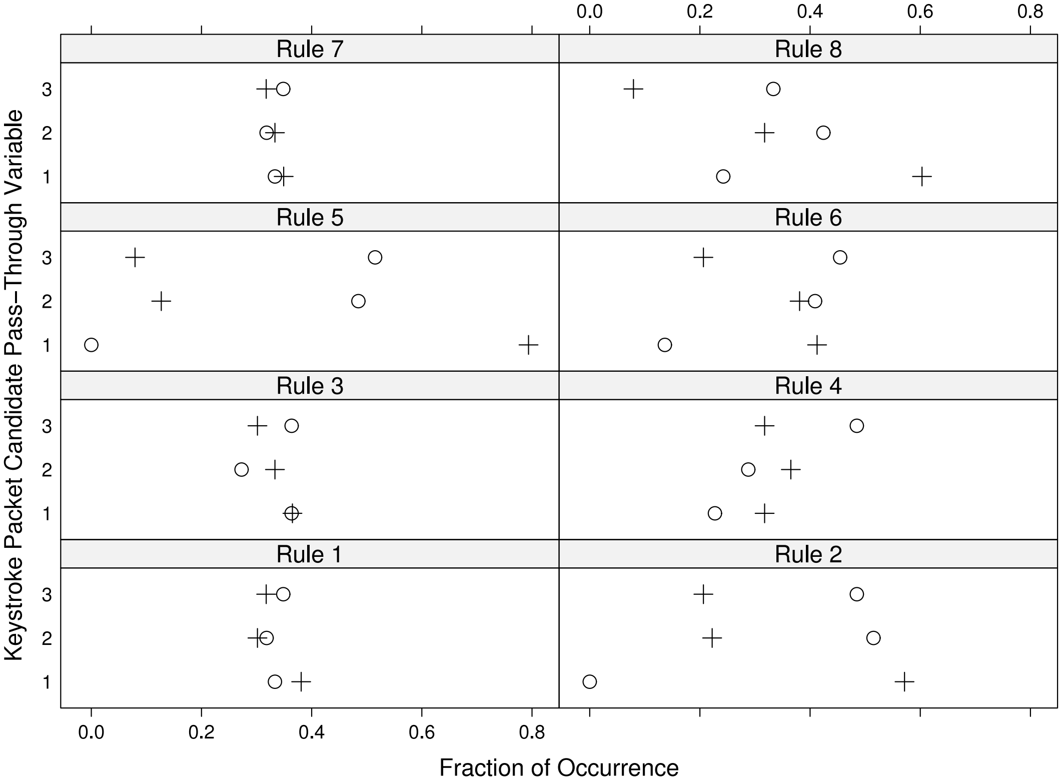


Table 2. Values of pass-through variables to minimize false positives and false negatives, but with a preference for greater control of false negatives.

Rule	1	2	3	4	5	6	7	8
Tuning Factor	$d_c^{(m)}$	$d_c^{(M)}$	$g_s^{(M)}$	$d_s^{(m)}$	$d_s^{(M)}$	$i_c^{(m)}$	$\ell_{cs}^{(M)}$	$g_{pc}^{(M)}$
Pass-Through Variable	1	2	2	3	3	3	1	1

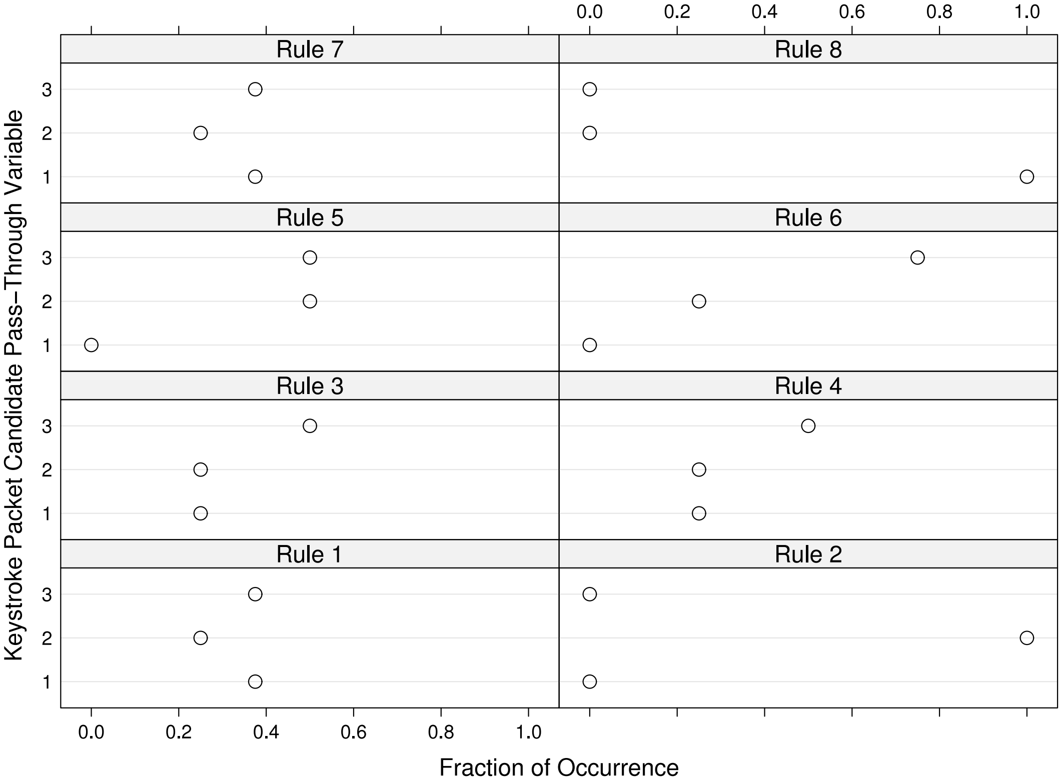
as we saw in Figure 2 as well. One run that is a very reasonable choice from the 8 runs is shown in Table 2 which has 2 values of the pass-through variable at level 2, and 2 each at levels 1 and 3, exactly balancing the pass-through.

5.5. Rule Impact

The previous discussion shows how the 4 responses depend on the statistical tuning factors over the ranges of values chosen in the experiment. However, this does not speak directly to the impact that each rule has on the classification. We studied the impact by analyzing the number of packets dropped by each rule. To do this we need a specific combination of values of the factors. Here, we will use the values in Table 2.

For each of Rules 1 to 8, the impact metric for the rule based on one connection is the number of client candidate packets dropped by the rule. If after application of a rule, no client candidates remain in the connection, then the values of the metric for any succeeding rules are 0. So the impact for a rule is more precisely a marginal impact given any previous rules.

FIGURE 3. For each rule, the fraction of occurrences of 3 levels of the pass-through variable for runs that are a partial compromise of false positives and false negatives, but with somewhat higher priority to control of false negatives.



The impact metric for a collection of m connections has m values for each rule. We compare the 8 distributions of values to assess rule impact for the collection. Here, we describe this comparison for the connections of Test Regimens 3 (non-interactive, port 22, $m = 174$) and 4 (non-interactive, not port 22, $m = 1275$).

We begin our comparison of the impact distributions of Regimen 4 by considering, for Rule k, the number of connections, N_k, out of 1275 with at least one packet dropped:

$$[(k)\, N_k] : [(1)\, 182], [(2)\, 1135], [(3)\, 65], [(4)\, 0], [(5)\, 51], [(6)\, 44], [(7)\, 21], [(8)\, 99].$$

This gives us certain information about the drop distributions. Let n_{ki} for $i = 1, \ldots, N_k$ be the positive values, ordered from smallest to largest, of the number dropped for Rule k. Each panel of Figure 4 graphs, $\log_2(n_{ki})$ against i/N_k for one k. So a fraction i/N_k of the values on the vertical scale are less than or equal to $\log_2(n_{ki})$. This conveys more information about the drop distributions. Rule 4 does not appear since it does not result in drops for any connection. Rule 2 has the largest impact by far. It dropped packets in 1135 of the 1275 connections, Rule 1 has the next largest impact, and then Rules 8 and 5. Rule 4 appears to have the least impact, with none of the connections affected.

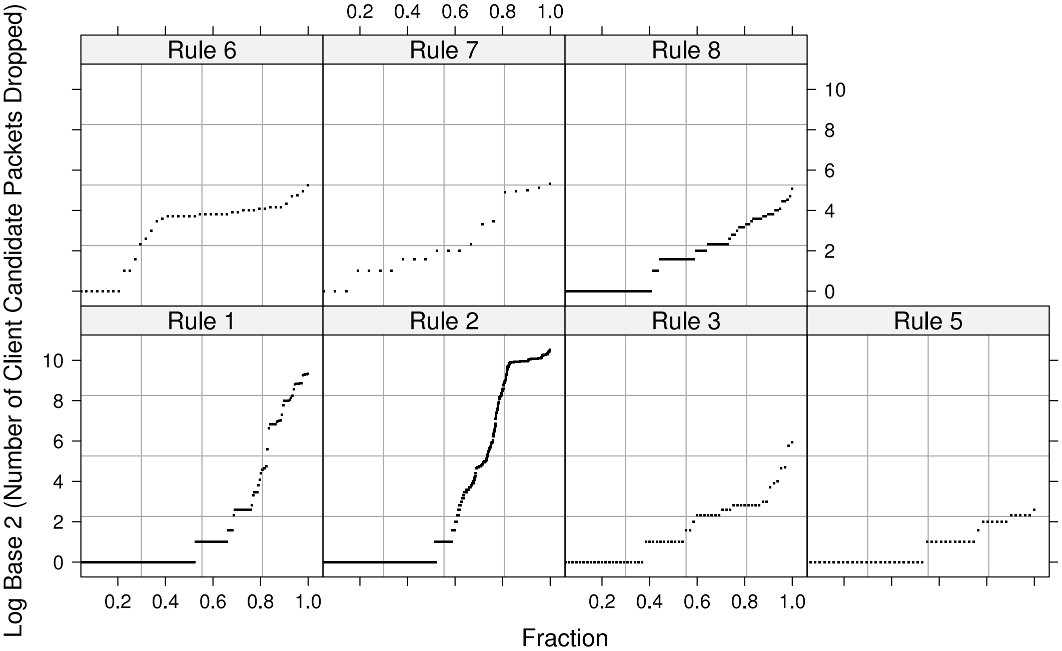
For Regimen 3, the following is the number of connections out of 174 with at least one packet dropped for each rule:

$$[(k)\, N_k] : [(1)\, 150], [(2)\, 173], [(3)\, 54], [(4)\, 0], [(5)\, 73], [(6)\, 168], [(7)\, 18], [(8)\, 174].$$

Figure 5 uses, for Regimen 3, the same display method as Figure 4. The impact of Rules 1, 2, 6, and 8 are quite substantial. Rule 4 remains as the one with no impact.

This methodology can be used to prune rules from the algorithm. For this analysis, Rule 4 is a candidate for deletion. However, it must be emphasized that for another choice of tuning parameters that balance false positives or false negatives in a different way, results could be quite different. Extensive study of impact in this way is beyond the scope of the paper.

FIGURE 4. Each panel plots the log base two of the nonzero counts of client keystrokes dropped by one rule for the 1275 connections from Test Regimen 4.



6. Testing the Keystroke Packet Classification

The methodology for Test Regimen 1 allows us to test the accuracy of the classification of client packets with data as keystrokes or non-keystrokes. The SSH connections of the regimen consist of 12 scripted interactive SSH sessions.

Each session was repeated 3 times for a total of 36 connections. All were carried out by one individual using a client outside the Purdue subnet and an SSH server inside the subnet. For each connection, the SSH packets and UDP key-press tracer packets were collected. The tracer packets are used as labels for the client keystroke packets. The streaming statistical algorithm was applied to each connection using statistical tuning factor values from Table 2.

Each of Sessions 1-3 consists of a single command resulting in a small number of packets. For example, one session is a command inquiring about the system version information.

```
uname -a <return>
```

Table 3 shows results for Sessions 1-3. There were no false positives or false negatives.

Each of Sessions 4-8 consist of multiple commands over several lines. Compared with Sessions 1-3, there are more keystrokes and sessions are longer. One session is a set of application development build commands.

```
cd tmp <return>
cd git-1.6.3.1 <return>
```

FIGURE 5. Each panel plots the log base 2 of the nonzero counts of client keystrokes dropped by one rule for 176 connections from Test Regimen 3.

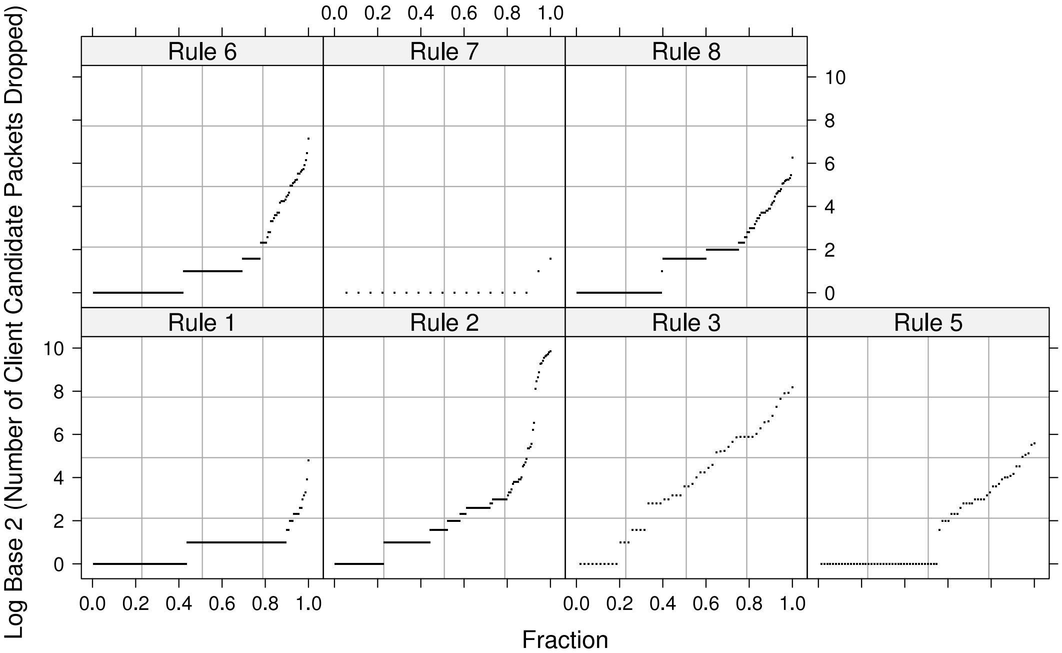


TABLE 3. Test Regimen: Results for Sessions 1 to 3

Session	Keystrokes	False Neg.	False Pos.	Client Data Pkts.	Client Pkts.	Server Data Pkts.	Server Pkts.
1	3	0	0	9	25	15	17
	3	0	0	9	26	16	18
	3	0	0	9	26	16	18
2	13	0	0	19	46	25	26
	13	0	0	19	44	25	26
	13	0	0	19	44	23	24
3	9	0	0	15	38	22	24
	9	0	0	15	37	21	23
	9	0	0	15	37	21	23

```
  ./configure <return>
```

Table 4 shows results for Sessions 4-8. There were no false positives or false negatives.

Sessions 9-12 were applications which themselves required users to type text, e.g., the `vi` editor. Editors also have key presses that are not keystrokes by our definition, but rather act as navigation or editing aids. For example, pressing the `j` key in `vi` command mode moves the cursor down one line. Table 4 shows results for Sessions 9-12. The causes of false negatives and positives for the session were the same for the 3 connections.

The single false negative in Session 9 (creating a document using the `emacs` editor), was a text creation character that also cleared the screen. Here, the data size of the server echo for this was larger than the maximum for Rule 5. The two false positives, (`[ctrl-x]` and `[ctrl-c]`) is the key press sequence to quit `emacs`.

Table 4. Test Regimen: Results for Sessions 4 to 8

Session	Keystrokes	False Neg.	False Pos.	Client Data Pkts.	Client Pkts.	Server Data Pkts.	Server Pkts.
4	32	0	0	38	84	45	47
	32	0	0	38	85	46	48
	32	0	0	38	84	45	47
5	53	0	0	59	262	202	204
	53	0	0	59	262	202	204
	53	0	0	59	264	204	206
6	31	0	0	37	452	414	416
	31	0	0	37	517	479	481
	31	0	0	37	518	480	482
7	203	0	0	209	462	252	254
	203	0	0	209	460	250	252
	203	0	0	209	462	252	254
8	173	0	0	180	1771	1591	1594
	173	0	0	180	1788	1608	1610
	173	0	0	180	1791	1611	1613

Session 11 consisted of launching `vi` and transcribing a paragraph. The first keystroke (corresponding to the first letter of the paragraph) was a false negative because its server acknowledgment did not contain data. This caused it to be rejected by Rule 4.

Session 12 consisted of browsing `man` pages and paging through the output of UNIX commands. One of the activities in this session was to search for a word in a `man` page. The search was initiated by pressing `/`, typing the search word and pressing `Enter`. The `man` program then found and highlighted the searched word. The packet corresponding to the `Enter` was rejected by Rule 5 because the server response was 1448 bytes. Of the three false positives, two were consecutive presses of the space bar to navigate to the following page and the third was the press of `q` to quit the `man` browser.

Table 5. Test Regimen 1: Results for Sessions 9 to 12

Session	Keystrokes	False Neg.	False Pos.	Client Data Pkts.	Client Pkts.	Server Data Pkts.	Server Pkts.
9	54	1	2	60	163	102	106
	54	1	2	60	165	104	108
	54	1	2	60	164	103	107
10	9	0	0	19	57	37	39
	9	0	0	19	57	37	39
	9	0	0	19	57	37	39
11	338	1	0	344	697	353	357
	338	1	0	344	697	353	357
	338	1	0	344	696	352	356
12	177	1	3	198	490	303	307
	177	1	3	198	489	301	305
	177	1	3	198	495	306	310

7. Past Work

There is a large literature on classifying connections using connection variables that have one value per connection and are based on information in the timestamps and in transport and IP headers. In this work, statistical and machine-learning methods are used to cluster connections or to classify them into categories such as interactive or non-interactive. [1, 2, 3, 4, 5, 6, 8, 9, 10, 18, 19, 20]. In contrast, our work performs differently by operating directly at the packet-dynamical level and identifying individual keystroke packets. We are unaware of any other past work on such packet-level keystroke detection.

Our work is most similar to research in detecting backdoors and stepping stone traffic. Zhang and Paxson[19] classify as interactive, connections with a high proportion of small packets with inter-arrival times in the range of 10 ms to 2 sec. Their algorithm also checks packet lengths for conformance to the SSH protocol: if 75% of the packets meet the specification, the connection is declared SSH. Timing analysis along with packet size has been used in the detection of stepping stones by Zhang [20], and in the detection of interactive terminal sessions over stepping stones by Yung [18]. Ding[4] estimated the full RTT for long chains in a stepping stone attack; using TCP sequence and acknowledgement numbers, it identified the interval from the end of the command output of the server to the next client input. Donoho[5] was able to demonstrate that even if traffic is jittered for purposes of evasion, there are theoretical limits on the ability of attackers to disguise traffic, and used a wavelet-based approach for multi-scale detection. This stepping stone detection sought to correlate the inbound and outbound connections of an intermediate stepping stone machine.

8. Discussion

8.1. Results

The algorithm succeeds because the keystroke and echo packets create an identifiable dynamical pattern. The size and timing relationships of these packets is clearly different from those which are seen for machine-generated traffic.

The SSH Protocol Rules I and II play an important role in the algorithm by dramatically reducing the number of connections under consideration. Here, the SSH handshake and encryption are our friends. The handshake requires at least 22 packets; then, we need client packets after that to serve as candidate keystrokes. Rule I, taking these two matters into account, eliminates the majority of connections from consideration. The sizes mandated for encryption create a stark length signature, and Rule II drops half of the remaining connections.

Only a very small fraction of connections remain, 0.16% for our Purdue subnet data. But because a human cyber security analyst eventually needs to resolve connections classified as interactive, and because we started in our case with about 1 million connections over 5 days, the 1680 remaining are far too many for the analyst. This is what makes the Packet-Dynamics Rules crucial. The formal testing, and the experiment to explore the effect of the tuning factors, reveal how thresholds can be set to reduce the connections to a manageable number.

Our success has arisen from working at the packet dynamical level. We believe this can be a fruitful approach in general for cyber security monitoring and forensics. Machine-to-machine communication appears to be full of distinctive dynamical patterns induced by applications, libraries, and other software layers, providing rich information for detection of subversive behavior.

8.2. Limitations

The Packet-Dynamics Rules use the timing characteristics of client data packets and their server responses. Their performance could suffer in conditions with much network congestion or where servers are overloaded. All of our experience to date has been on networks where there does not appear to be substantial jitter of the packet timings during an individual connection; and servers are not so burdened as to have to defer generating echoes. We have tried informally to stress the algorithm by using stepping stones on remote networks, but formal testing is warranted.

Of course attackers will try to evade detection by the algorithm. Typical behavior is to follow a path of least resistance, for example, SSH under current surveillance conditions. If our algorithm and others like it became widespread, then attackers have the motivation to evade, but not otherwise. And then the algorithm needs to change, but until evasion occurs, there is no motivation to do so.

The SSH protocol permits the multiplexing of data streams within a single active connection through a variety of tunneling mechanisms. One example is multiple `xterm` windows using a single SSH tunnel. This could result in keystroke traffic being shrouded by other data. A attacker could use this to hide.

Other example evasions can be seen when we divide the rules into two rough groupings. *Size:* Rules 1,2,4,5 identify candidate keystrokes by packet size ranges; *Timing:* Rules 3,6,7,8 identify timing characteristics of interactive traffic.

In *Timing*, Rule 6, which depends on the cadences derived from the human factors of typing, can be directly attacked using an unmodified SSH client if the session is launched with the "-T" flag. This prevents the server from allocating a pseudo-tty and forces the client program to assemble keystrokes into entire lines of input before sending them to the server. However, this has significant negative consequences for the attacker because the session no longer appears interactive at the server. Many commands useful for *ad hoc* exploration will simply not work or have their function severely reduced.

To evade *Size* constraints a skilled attacker, one who is able to modify his SSH client code, can convince the algorithm that the session is non-interactive by padding all keystroke packets to have lengths larger than the maximum client packet size in Rule 2. Such padding would have to be carefully done so as to be trimmed off again by the server's message unpacking code.

8.3. Implementation in the Argus Traffic Audit System

For it to be useful for everyday network security, our algorithm needs to be part of a network traffic monitor operating in realtime. To this end, we are collaborating with Qosient, LLC (http://qosient.com) to imbed the algorithm in their Argus network traffic sensor. Argus is widely deployed in commercial, government, and educational settings. It has been used to monitor extremely high-speed networks in realtime. The bidirectional architecture makes it well-suited as a platform for packet dynamics. Argus has long had features for measuring packet loss, jitter, and round-trip times in monitored traffic.

The most recent version, Argus 3, adds flexible mechanisms which permit additional attributes to be calculated for connections. We leverage this facility for keystroke detection. The prototype code, now in pilot deployment, consisting of a few hundred lines of C. A few dozen lines constitute the heart of the code which runs over a window consisting of only the previous candidate and current packets. The rest consists of setup, debug tracing, and a small queue which accounts for out-of-order packet arrival.

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