Memory and Data Access Privacy

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Abstract

In this paper, we explore a novel way of invading computer-usage privacy. By examining the memory addresses of the requests to RAM and hard drive, we show that it is possible to extract information about the program that is running.

1 Introduction

With the popularization of virtualization technologies and decreasing cost of server co-location maintenance, an increasing number of servers are being moved to third party managed virtual machines somewhere on the cloud. While this modern approach to solving the economic dilemma of controlling company revenue spend on on-site technical staff does contain attractive benefits, it unfortunately opens the door to many complications that are introduced in the process of preserving the integrity of sensitive customer data in a potentially hostile IT environment. As a result, the field of providing easy to implement fundamental precautionary solutions for the protection of confidential information is continuously developing and encryption of data transfer channels finds it place at the heart of the most essential toolkit that is available to every system administrator. Unfortunately, while encryption can certainly provide a level of data integrity protection, the fact that server physical access is available to maintenance technical staff that could be considered an untrusted source that can exploit its practically unlimited physical access to the hardware raises the issues of examining the efficiency of data encryption against hardware related attacks. In particular we would focus on the case where the previously mentioned untrusted party represented by the co-location technical staff is able to successfully install a hardware device that is able to record memory and disk requests. This device could then be exploited by the attacker to obtain actionable intelligence about the inner working of specific applications on the clients server.

2 Overview

To obtain sensitive information from a particular application through the exploitation of **memory traces**[1] and **disk traces**[2], an attacker must first be able to fingerprint the application of interest and recognize or compile a set of data related to the targeted application's normal operational behaviors. Once such dataset of application specific actions has been generated, a potential attacker would have a sufficient foundation to explore various data mining techniques by which he/she might

[1]Requested memory addresses that missed in the lowest level of cache, along with the associated type of request (instruction read, data read, data write).

[2]Block read/write requests

be able to compare, match, analyze and eventually extract viable information from the signature traces from the targeted machine.

For this project, we gathered information using the software tools Cachegrind and blktrace rather than tampering into actual hardware. In addition, we assumed single processes running on single CPUs. Depending on the program that we chose to attack, we developed different ways of analyzing the traces to form possible attacks, which we discuss further in the following sections.

3 SVN Version Control Analysis

3.1 Application Overview

We chose an SVN server as the application to analyze. An attack on our application would constitute being able to determine which SVN commands are being performed at a given time or which or how many files are being modified. Due to the nature of our application, we decided that a disk trace would bear more fruitful results and would be more helpful in determining if our application could be attacked. The disk tracing utility that we used to gather our data `blktrace` provided us with a disk trace while the SVN server executed some command. However, we had to simulate the SVN server commands on our own on an Amazon EC2 instance. The output of blktrace contains the location and size of disk reads and writes each associated with a timestamp and process name.

3.2 Analysis Process

To provide a dataset for our tests we wrote a series of scripts to generate files of specified number and size with randomized data taken from /dev/ urandom. We primarily considered files in the size range 1-10KB, which we settled on as a reasonable approximation of the size of source files, which would be placed under version control in practice. We traced operations on data sets as small as one file and as large as 1000. By clearing the file system cache and filtering for traces originating from the SVN server, we were able to recover a detailed record of the disk operations requested by SVN.

3.3 Tools and Results

Our method of analyzing the traces was different from the other groups because we did not rely on the addresses of our disk accesses in order to determine the locality of the files being accessed. Instead of this, we tried to establish access patterns by looking at the individual operations themselves. In our case, we were dealing with different files in different locations, and since modifying the files results in reading/writing a large disk block, it was difficult to find consistent locality patterns. Due to this difference, we opted to establish disk access patterns by looking at the individual operations of the traces and comparing chunks of these operations present between traces to determine differences between commands.

We were able to come up with a few vulnerabilities in the SVN server as well as the attacks that are a result of these vulnerabilities. We were fairly successful in distinguishing between SVN commands. Our basic approach was to analyze the number of reads versus writes over time, both by dividing the trace into segments and calculating read/write percentages and by simply graphing reads and writes over time. We were able to distinguish read-heavy commands such as checkout from write-heavy commands such as add. We were also able to find a very distinctive pattern characteristic of the delete command, allowing us to distinguish deletes from other mixed read/write operations. We attempted to find a relationship between the number of SVN IO requests necessitating disk seeks and the number of files being transferred or updated, but the correlation proved to be weak at best and results varied excessively with repeated trials. This may have been the result of file system fragmentation, interference from non-SVN processes, or access pattern optimizations beyond our direct control.

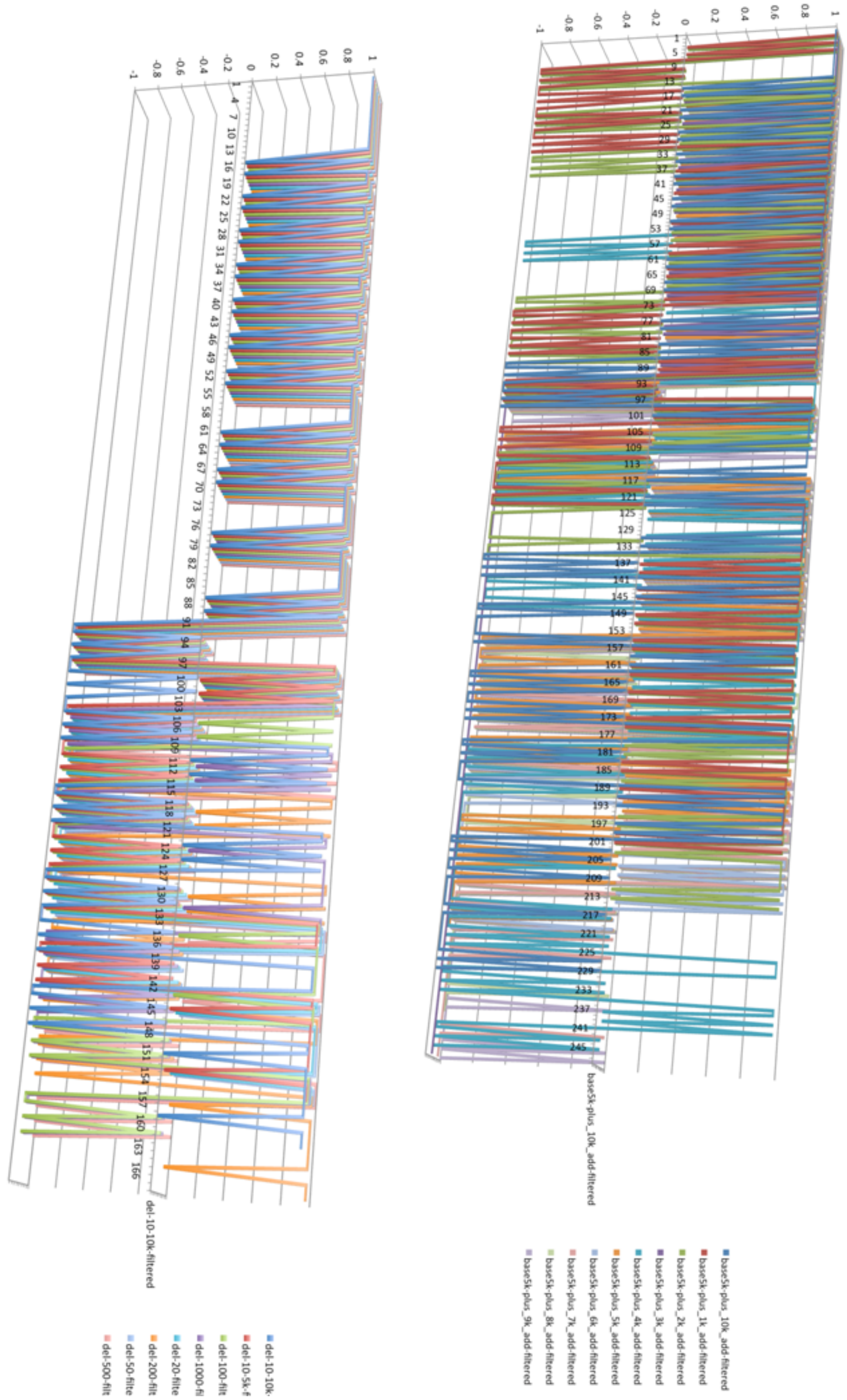


Figure 1: Disk access graphs

Figure 1(a) compares delete traces of different file sizes (the sizes can be seen in the legend on the right). The y-axis indicates whether the operation within the trace is a read (1), write (-1) or disk idle time (0). The x-axis indicates the line number of the delete traces filtered for IO requests generated by the SVN server. The fact that many of the operations of the traces overlap in chunks at the beginning shows us that regardless of the file size, these chunks of operations should be common to all delete traces. We can use this distinctive pattern to differentiate the delete command from the other SVN commands.

Figure 1(b) compares the traces of a 5kB size file and the same file with 1-10kB of random data added to the end of the file. The x and y axis on this graph represent the same things as in the previous one. These files represent the effect of committing changes to a file. Comparing the two graphs we can see that the first halves of both bear similarities in the chunks of reads that overlap between traces. However, in the second half of the right graph, we see that there is a large amount of noise as well as a substantial number of reads (as supposed to the first graph of the delete traces which had a large number of writes in its second half). Therefore, this difference in the second half of the graph enables us to differentiate between a differential commit and a delete command (given our data set).

4 IRC Server Analysis

4.1 Application Overview

This part of the project focused on an IRC daemon and its memory access patterns. Although IRC is not a particularly secure means of communication, we feel that this attack is representative of a class of attacks that could be applied to most programs. Our attack on Dancer-IRCD should be regarded as a proof-of-concept.

We made an attempt to identify common tasks users perform when interacting with the server. If we can identify commands being run on an IRC server, then it should be possible to identify commands being run on other application servers. The tests were performed on Dancer-IRCD, a relatively common IRC server. We used the modified version of chachegrind to record memory accesses. In particular, we collected memory traces for seven commands: connect, list, create room, quit, join, kick, and part. We then created a classification algorithm that was able to correctly predict all unknown commands from a validation set.

4.2 Analysis Process

The first challenge we faced was that the IRC server fit almost completely in the CPU cache. We had to reduce the cache size used by Valgrind to 32KB level 1 instruction and data caches, and a 64 KB level 2 cache in order to get meaningful results, since with any larger size cache we were not able to get any memory accesses in some situations.

Initially, we had written a simple IRC client that played random messages of varying lengths onto the server and recorded the results automatically, but we found that we could not conduct meaningful analysis on the data collected this way. Instead, we realized that it would be more efficient to generate memory traces for each command we were going to try and detect. This was done manually using an existing IRC client (irssi), where we repeatedly executed the same commands and recorded the corresponding accesses.

We trained our command classifier on a set of memory traces corresponding to that command. For each command we took the intersection of the memory addresses from the traces in that command's training set. Our first attempt at classification was to take the intersection of the trace from an unknown command, and the subset associated with a command. Whichever command had the highest ratio (matched addresses/total addresses) was declared to match.

An issue occurred when a command had few identifying features that were contained in a larger set of features for another command. The algorithm would classify the trace as the command with the smaller feature set, even though the trace actually corresponded to the command with the larger feature set.

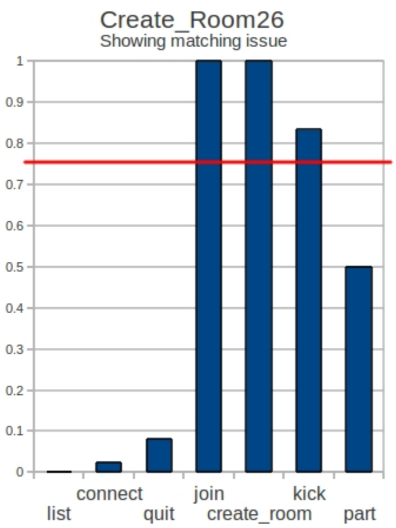
To solve this problem, we realized that it would make sense to start with the largest feature set first. If a match was found for a large command set with a certainty above a specified threshold, the algorithm would stop searching and declare a command found. If no command reached the threshold, the highest rated command would be used. We set the threshold at 0.75, based on trends we saw in the data. In almost all cases, if a command was matched with at least 0.75 accuracy, then it was likely correct. Another way to address this issue was to increase the training set size. With a training set of ten memory traces per command, this issue became negligible.

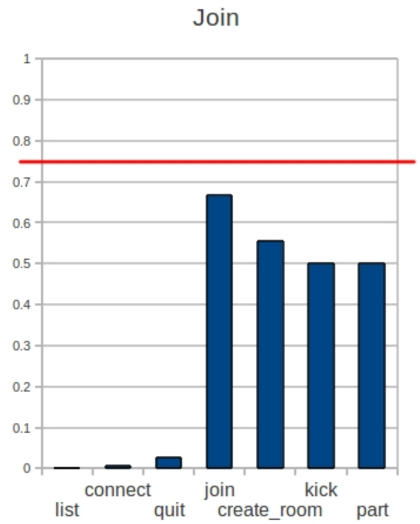
4.3 Tools and Results

From the data that the matching program output, we generated graphs to visualize our results. The program runs the intersecting set for each command against command to be classified, and outputs a likelihood for the commands. The largest of these is the matching result in most cases. However, very occasionally there would be more than one commands with equal probabilities, or values above the cutoff. For these, the solution was to sort by size and pick the larger one, as described in the analysis section. The sample shown below illustrates the issue, where both join and create room have the same probabilities.

The rest of the graphs show examples of the respective commands, where we did not strictly require the sorting part of the process to obtain the correct result.

We were able to correctly classify 69/70 of the commands in the verification set. We classified create room with 90% accuracy, and all other commands with 100% accuracy. For the probabilites assigned to each command, see irc_ results.odg in the supplemental code submission.


Create_Room26
Showing matching issue
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
list
connect
quit
join
create_room
kick
part


Join
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create_room
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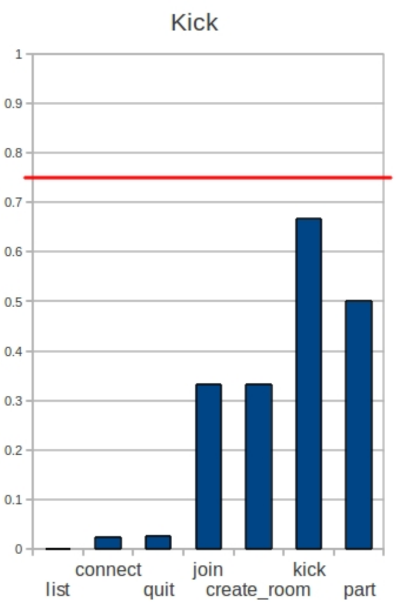
Kick
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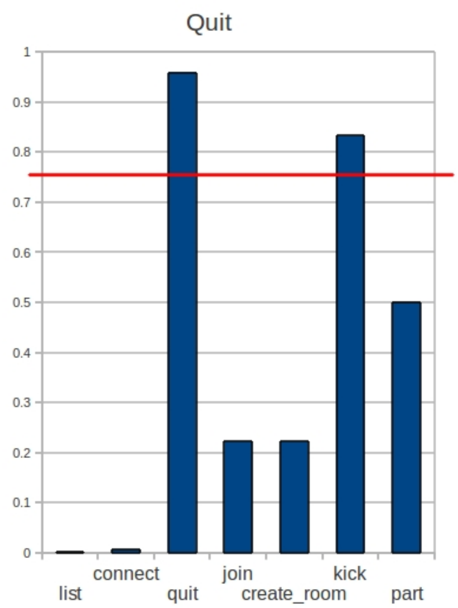
Quit
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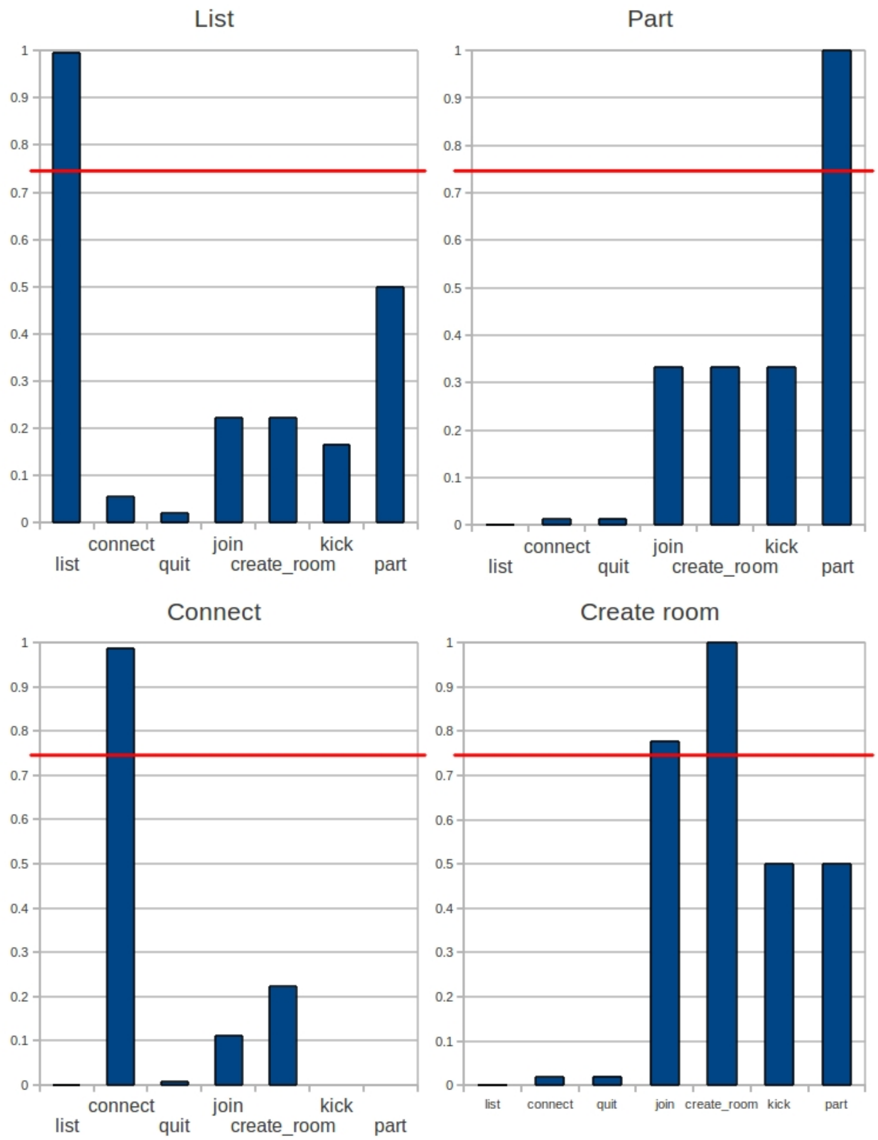
create_room
kick
part



4.4 Conclusion

We were able to successfully recognize all seven commands we issued to an IRC server with a high degree of accuracy, while using only a simulation of the addresses available on the memory bus. However, to achieve this, we had to decrease the cache size so that we could observe memory accesses. To extrapolate from this result, a memory bus based attack seems possible for programs that have executables significantly larger than that of Dancer-IRCD.

5 Squid[3] Proxy Analysis

5.1 Application Overview

Web proxies can improve performance by caching commonly visited websites into memory or disk and retrieving the web page data on subsequent requests to that page. It is this functionality that we hope to use in an attack. On cache misses, we should see memory accesses to store the resources. On cache hits, we expect to see memory accesses back to the previously visited address. If we can figure out this mapping from memory location to resource, we would be able to figure out when someone is accessing a specific resource, like a site-key image. This attack would completely bypass the TLS protection that makes HTTPS secure.

We chose Squid over other web proxies because it is widely available and well known. In addition, Squid is open source and can run as a single process daemon, which makes it easier (for us) to analyze the memory traces.

5.2 Attack Strategy

Our proposed strategy was to start Squid with an empty cache, access a web page, and figure out which memory addresses were accessed. Then we would access a new web page and find the memory addresses unique to each request. From this we should be able to generate features unique to those web pages. To prevent the CPU cache from storing everything internally, we flood the CPU cache with a large sequence of HTTP requests in between accesses.

By reading the documentation on Squid, we found out that Squid caches objects both in-memory and on-disk, so we gathered both memory traces and disk traces.

5.3 Memory Traces

We first looked for a correlation between requests to the proxy and memory accesses. Our primary test workload consisted of two cases—one where a client accessed a sequence of Wikipedia articles resulting in only cache misses and one where a client accessed a sequence of Wikipedia articles twice, resulting in a sequence of misses followed by a sequence of hits.

Unfortunately, when we first collected traces, we discovered that due to the large CPU cache size, there were almost no accesses to main memory after Squid finished initialization. In a real attack, this would be less of an issue as the cache would be invalidated by context-switching and would be under greater load; in order to simulate this, we decreased the effective L2 cache size from 8MiB to 64KiB.

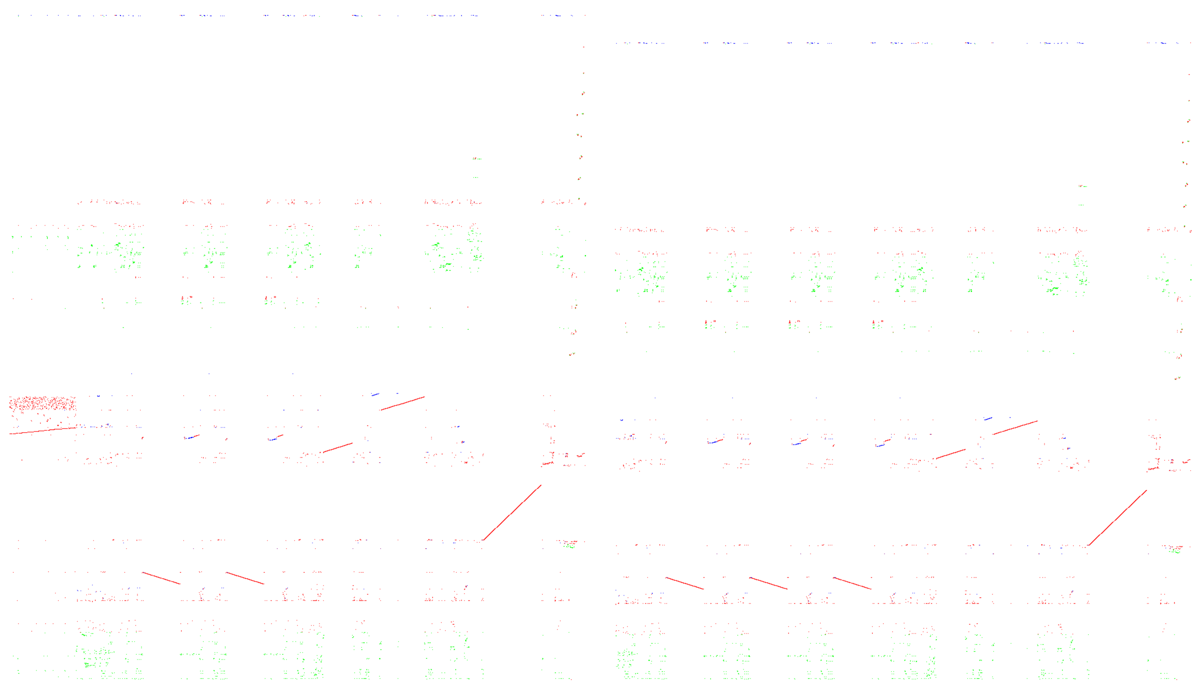
Running the traces again, we were able to get a more representative view of Squid's memory access pattern, as shown in Figure 2.

However, comparing the two workloads, we weren't able to make out any discernable difference in their access patterns. After reading through the Squid API documentation, we learned that Squid makes heavy use of memory pools to avoid internal memory fragmentation.[4]

As a side-effect, Squid exhibits very good cache locality and thus still makes relatively few accesses to main memory, and when it does, the addresses are from the same shared memory pool. As a result, we concluded that it would be impractical to try to map content to addresses in Squid's in-memory cache.

[3] Version 3.1

[4] `http://www.squid-cache.org/Doc/code/group__MemPoolsAPI.html`



(a) Memory pattern after accessing 100 Wikipedia sites (b) Memory pattern after accessing 100 Wikipedia sites, and then hitting the same 100 sites again.

Figure 2: Relative memory access patterns. One pixel on the x-axis is roughly 100 or so instructions. The y-axis shows relative memory accesses (not to scale). The graphs show the last 5000 memory traces. (Thus, the left side of Figure 2(a) is part of initialization.)

5.4 Disk Traces

Being unable to get any useful information from memory traces, we turned to collecting disk traces. Since Squid uses disk in addition to memory to cache data, we should be able to make some rough mapping from a site to a block sector. To get block traces, we ran the Linux tool `blktrace` after Squid had initialized and accessed 1000 Wikipedia sites (totalling 180 MB worth of data). However, the block traces that we got showed only a read operation happening on the disk every 15 seconds, which was no different from the access pattern that we got for not visiting any sites.

We are unsure the cause of this read that occurs every 15 seconds—our current theory is that it is looking at metadata. However, the cause of the reads are less important than the cause of the lack of writes; if we accessed a thousand sites without getting a write operation, mapping resources to disk blocks would nigh impossible, since we would need to know what data has been written into the disk block, which is not necessarily linked to the requested website that caused Squid to write to disk.

5.5 Conclusion

As a result of Squid memory optimizations and powerful computers, we were not able to find any unique patterns to correspond to resources being loaded. Squid's memory management not only achieves better performance, but it also obfuscates the memory access pattern. In addition, the large size of caches and block sectors in today's computers make it hard to even get any traces for small requests. Exploiting Squid may be possible with an even larger set, but it is unlikely that we would be able to find a correlation between resources and memory accesses.

6 MySQL Analysis

6.1 Generating Signatures

6.1.1 Generate traces from target behaviors

As there are many various caching buffers that could potentially influence the amount of data that is being spilled from the CPU/RAM data bus, a flexible cache simulator with adjustable cache size is essential to this step of the data collection process. Our custom version of Cachegrind proved sufficient for providing us with relevant data once we realized that in order to avoid any parasitic hardware caching, its cache step size would need to be adjusted incrementally between 32KB and 12MB. This technique allowed us to successfully capture any instance of MySQL behavior related to moving data from and to disk. Our iterative analysis led us to believe that each target behavior will need anywhere between 5 to 10 runs on average. That in order to get optimal signatures, filling the cache to different levels with data due to random application operations before each trace is performed and stored on disk would be a necessary. In addition, we noted that fewer traces are needed with a smaller cache size as the data outputted by the simulator seemed to be inversely proportional to the cache size. Finally, to help improve our performance we decided to discard instruction reads and data writes from all traces as their inclusion seemed to not significantly influence our results. Once completed you will have M sets of N traces:

$$\{T_{1.1}, T_{1.2}, \ldots, T_{1.N}\}, \{T_{2.1}, T_{2.2}, \ldots, T_{2.N}\}, \ldots, \{T_{M.1}, T_{M.2}, \ldots, T_{M.N}\}$$

.

6.1.2 (Optional) False positive reduction

Create another trace that contains other common application behaviors that are not being targeted. This will be used later to reduce the number of false positives and is mainly needed when the application has other behaviors similar to one of the target behaviors.

6.1.3 Maximize the set of possible tokens

To maximize the set of tokens[5] that make up each trace, perform a union on all traces of a given behavior. We will call the result the intermediate signature (IS).

$$\begin{aligned}
IS_1 =& T_{1.1} \cup T_{1.2} \cup \ldots \cup T_{1.N} \\
IS_2 =& T_{2.1} \cup T_{2.2} \cup \ldots \cup T_{2.N} \\
&\vdots \\
IS_M =& T_{M.1} \cup T_{M.2} \cup \ldots \cup T_{M.N}
\end{aligned}$$

6.1.4 (Optional) Finer grained features

Some features may have several methods of execution. For a SQL server the attacker may want to know when a query with count() is called. The attacker would generate γ queries containing this function but this would cause the resulting union to be huge and containing a lot more data than just count. The solution is to run N traces of each variation containing this function, union each

[5] Memory addresses and access type from target behavior memory trace

variation and then intersect the resulting unions.

$$IS_x = \bigcap_{i=1}^{\gamma} \bigcup_{j=1}^{N} T_{x.i.j}$$

6.1.5 Eliminate similarity between targeted behaviors

It is possible that many of the target behaviors access many of the same addresses as other targeted behaviors (also step 1.1 behaviors). To eliminate the similarities we will compute the set difference of each IS to all other ISs. The resulting signature will be represented as S.

$$\begin{aligned}
S_1 =& (((IS_1 - IS_2) - IS_3) \ldots - IS_M) \\
S_2 =& (((IS_2 - IS_1) - IS_3) \ldots - IS_M) \\
& \vdots \\
S_M =& (((IS_M - IS_1) - IS_2) \ldots - IS_{M-1})
\end{aligned}$$

6.2 Analyzing a Live Application Trace

Step through a live trace (standard cache size) with a predefined step length. The step size needs to be reasonable, anywhere from 20 - 200 should be sufficient. The step size will need to be finessed till predictions as close a possible to what is actually taking place. For each step create a set β of all the memory accesses within that step. And compute the overlap coefficient of this set and each of the signatures.

$$\text{Overlap Coefficient} = \frac{|X \cap Y|}{min(|X|, |Y|)}$$

So for our purpose we get:

$$\text{Chance of feature in step} = \frac{|\beta \cap S_x|}{min(|\beta|, |S_x|)}$$

Safe each feature to separate files and plot the results.

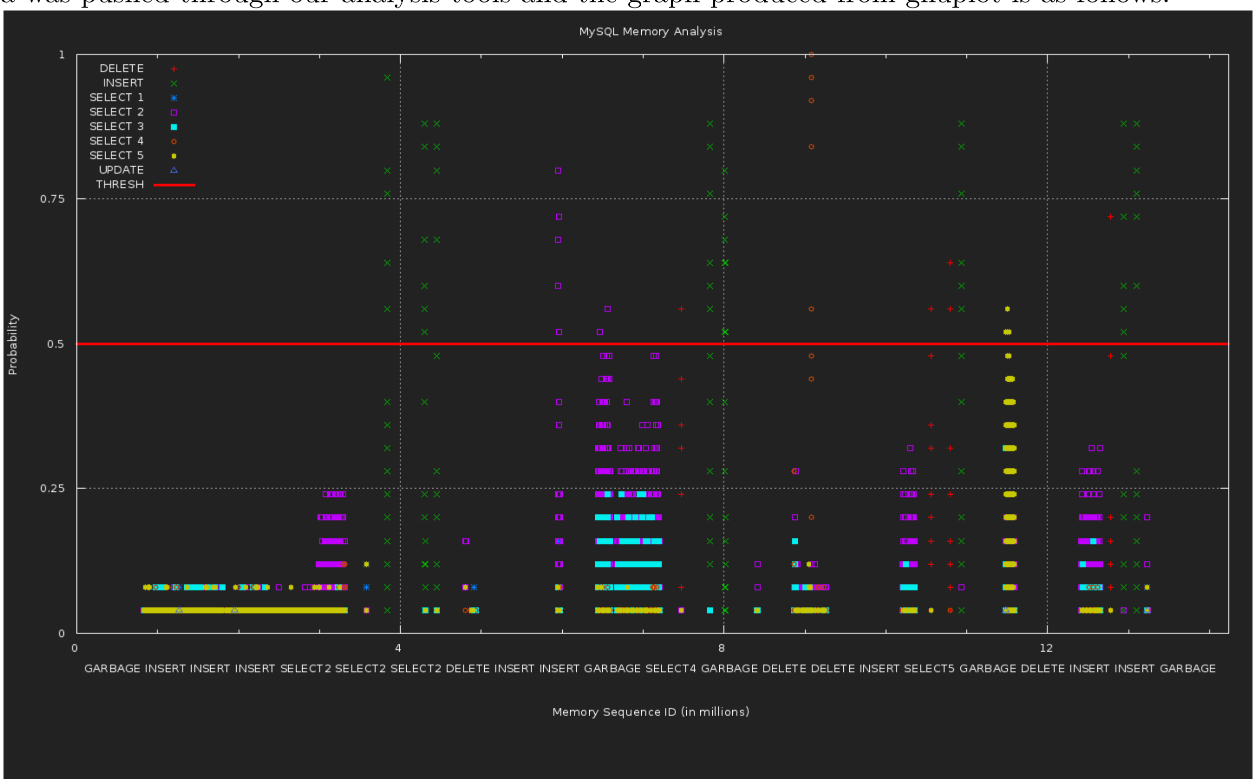
6.3 Sample Workload and Results

In the course of this project's time frame we were able to generate and collect a large amounts of diverse data traces that were used as a training data set of our analysis algorithm. One such workload is the fallowing SQL query list:

INSERT1 $\Longrightarrow$ insert into urls (url) values("testing1.com");
INSERT1 $\Longrightarrow$ insert into urls (url) values("testing1.com");
INSERT1 $\Longrightarrow$ insert into urls (url) values("testing1.com");
SELECT2 $\Longrightarrow$ select title from ebay_listings where BuyItNow > 2000;
SELECT2 $\Longrightarrow$ select title from ebay_listings where BuyItNow > 2000;
SELECT2 $\Longrightarrow$ select title from ebay_listings where BuyItNow > 2000;
SELECT2 $\Longrightarrow$ select title from ebay_listings where BuyItNow > 2000;
DELETE1 $\Longrightarrow$ delete from urls where url like '%testing1.com%';
INSERT1 $\Longrightarrow$ insert into urls (url) values("testing1.com");

INSERT1 $\Longrightarrow$ insert into urls (url) values(”testing1.com”);
SELECT4 $\Longrightarrow$ select title from purchases where price $>$ 2000;
DELETE1 $\Longrightarrow$ delete from urls where url like ’%testing1.com%’ and url.id = ’308924’;
DELETE1 $\Longrightarrow$ delete from urls where url like ’%testing1.com%’ and url.id = ’308925’;
INSERT $\Longrightarrow$ insert into urls (url) values(”testing3.com”);
DELETE1 $\Longrightarrow$ from urls where url like ’%10.50.50.174%’;
INSERT1 $\Longrightarrow$ insert into urls (url) values(”testing1.com”);
INSERT1 $\Longrightarrow$ insert into urls (url) values(”testing1.com”);

Though this query set may seem compact, the individual queries were interleaved randomly with large amounts of garbage data that was used to flush our simulator’s cache. The collected data was pushed through our analysis tools and the graph produced from gnuplot is as follows:



As you can see after extensive feature training our data analysis tools are able to predict quite accurately the order and type of instructions executed ragardless of the presence of noisy data.

6.4 Final Remarks

Ever since the popularization of the LAMP stack framework to enterprise production environments, the question of whether or not an open source tool like MySQL would be able to meet the fast paced demanding IT infrastructure has existed. An argument that practice has put to the test as many companies are becoming aware of the economical benefit that this product can provide over its commercial big brother Oracle. Moreover, as both of us have experience with developing on production implementations of the LAMP stack, we felt that this project would allow us to get an insight to any fundamental flows that MySQL might express under hostile infrastructure conditions and better understand of how this unwanted side effects could be resolved. With that motivation, we tried to simulate our development environment as close as possible to the one present in real world situations. We used reasonable assumptions, like the ability of potential perpetrator to install an external memory tracing device that would be able to listen to traffic on our server's memory bus. Its ability as a representative of the hardware maintenance team to exercise certain authority over machine's application platform running processes as root and being able to collect application data. All reasonable privileges that in the end proved arguably sufficient to our successful ability to analyze our data. So what were we able to deduce after four months of exploiting every avenue for extracting any exploitable information from a company's MySQL server that might be running under the supervision of an untrusted third party:

1. We found that given a large well tailored dataset of application specific operation's traces, we were able to predict whether or not the operation was performed. For example, we can figure out if a query with a specific logical syntax was performed. Examples are :

```
SELECT ____ FROM ____ WHERE ____ = ____ ;
SELECT ____ FROM ____ WHERE ____ > ____ ;
SELECT ____ FROM ____ WHERE ____ LIKE ____ ;
```

2. We can differentiate between the different type of SQL operations `SELECT`, `INSERT`, `DELETE`, `UPDATE`, etc.

3. Though not able to pinpoint what table names, column names or data fields were being utilized within the queries, given more time we feel that as long as the data stream is not encrypted, we could potentially extract more query specific information as our initial goal was close to recovering database schema.

In summary, our part of the overall project proved sufficient to provide a good a foundation for a potentially more fine grained area of research on the topic. We feel that improving the current algorithm for analyzing the trace data would yield more descriptive results. However, we fear that such implementation could result into a solution with exponential running time. In addition, we believe that incorporating DNA analysis and plagiarism related analysis implementations would serve a good starting point for producing a more accurate data mining results. Finally, we feel convinced that if potential attacker is familiar with the database setup, which given the fact that MySQL is open source , and for example PrestaShop is also an open source online store application often installed with MySQL backend, data integrity exploitation is a possible treat. Moreover, since we were able to differentiate between MySQL operations, we believe that an attacker can successfully gain knowledge of the real workload of the latter mentioned host, which in turn would provide information to when would be the best time a memory trace should take place. Something that we are convinced the owner of the machine would not be happy to openly disclose. Though we did not have enough time to completely exploit the previously mentioned scenario, we have no doubt that the treat of information leakage is as present as ever and that the topic should be extensively researched as the popularity of Web-based applications and economically beneficial MySQL integrations is continuously increasing.