# The Spy in the Sandbox – Practical Cache Attacks in Javascript

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# **Abstract**

We present the first micro-architectural side-channel attack which runs entirely in the browser. In contrast to other works in this genre, this attack does not require the attacker to install any software on the victim's machine – to facilitate the attack, the victim needs only to browse to an untrusted webpage with attacker-controlled content. This makes the attack model highly scalable and extremely relevant and practical to today's web, especially since most desktop browsers currently accessing the Internet are vulnerable to this attack. Our attack, which is an extension of the last-level cache attacks of Yarom et al. [23], allows a remote adversary recover information belonging to other processes, other users and even other virtual machines running on the same physical host as the victim web browser. We describe the fundamentals behind our attack, evaluate its performance using a high bandwidth covert channel and finally use it to construct a system-wide mouse/network activity logger. Defending against this attack is possible, but the required countermeasures can exact an impractical cost on other benign uses of the web browser and of the computer.

# 1 Introduction

Side channel analysis is a remarkably powerful class of cryptanalytic attack. It lets attackers extract secret information hidden inside a secure device by analyzing the physical signals (power, radiation, heat, etc.) the device emits as it performs a secure computation [15]. Allegedly used by the intelligence community as early as World War II, and first discussed in an academic context by Kocher et al. in 1996 [14], side channel analysis has been shown to be effective in breaking into myriad realworld systems, from car immobilizers to high-security cryptographic coprocessors [8, 18]. A particular kind of side-channel attack which is relevant to personal computers is the cache attack, which exploits the use of cache

memory as a shared resource between different processes or users to disclose secret information [17, 11].

While the potency of side-channel attacks is established without question, their application to practical systems is relatively limited. The main limiting factor to the practicality of side-channel attacks is the problematic **attack model** they assume: with the exception of network-based timing attacks, most side-channel attacks require that the attacker be in close proximity to the victim. Cache attacks, in particular, typically assume that the attacker is capable of executing arbitrary binary code on the victim's machine. While this assumption holds for Infrastructure/Platform-as-a-Service (IaaS/PaaS) environments such as Amazon's cloud computing platform, it is less relevant for other settings.

In this report we challenge this limiting security assumption by presenting a successful cache attack which assumes a far more relaxed and practical attacker model. In our attacker model, the victim merely has to access a website owned by the attacker. Despite this minimal attack model, we show how the attacker can still launch an attack in a practical time frame and extract meaningful information from the system under attack. Keeping in tune with this computing setting, we chose to focus our attacks not on cryptographic key recovery but rather on tracking user behavior. The attacks described in this report are therefore highly practical: practical in the assumptions and limitations they cast upon the attacker; practical in the time they take to run; and practical in terms of the benefit they deliver to the attacker. To the best of our knowledge, this is the first side-channel attack which can scale effortlessly into millions of targets.

For our attacks we assume that the victim is using a personal computer powered by a late-model Intel CPU. We furthermore assume that the user is accessing the web through a browser with comprehensive HTML5 support. As we show in Subsection 5.1, this covers a vast majority of personal computers connected to the Internet. The victim is coerced to view a webpage containing an attacker-

controlled element such as an advertisement. The attack code itself, which we describe in more detail in Section 2, executes a Javascript-based **cache attack**, which allows it to track accesses to the DUT's last-level cache (LLC) over time. Since this single cache is shared by all CPU cores and by all users, processes and protection rings, this information can provide the attacker with a detailed knowledge of the user and the system under attack.

# 1.1 The Memory Architecture of Modern Intel CPUs

Modern computer systems typically incorporate a highspeed central processing unit (CPU) and a large amount of lower-speed random access memory (RAM). To bridge the performance gap between these two components, modern computer systems make use of cache memory - a type of memory element with a smaller size but a higher performance, which contains a subset of the RAM which has been recently accessed by the CPU. The cache memory is typically arranged in a cache hierarchy, with a series of progressively larger and slower memory elements being placed in levels between the CPU and the RAM. Figure 1, taken from [22], shows the cache hierarchy used by Intel Ivy Bridge series CPUs, incorporating a small, fast level 1 (L1) cache, a slightly larger level 2 (L2) cache, and finally a larger level 3 (L3) cache which is then connected to the RAM. The current generation of Intel CPUs, code named Haswell, extends this hierarchy by another level of embedded DRAM (eDRAM), which is not discussed here. Whenever the CPU wishes to access a memory element, the memory element is first searched for in the cache hierarchy, saving the lengthy round-trip to the RAM. If the CPU requires an element which is not currently in the cache, an event known as a cache miss, one of the elements currently residing in the cache must be evicted to make room for this new element.

The Intel cache micro-architecture is **inclusive** – all elements in the L1 cache must also exist in the L2 and L3 caches. Conversely, if a memory element is evicted from the L3 cache, it is also immediately evicted from the L2 and L1 cache. It should be noted that the AMD cache micro-architecture is exclusive, and thus the attacks described in this report are not immediately applicable to that platform.

This report focusses on the level 3 cache, commonly referred to as the last-level cache (LLC). Due to the LLC's relatively large size, it is not efficient to search its entire contents whenever the CPU accesses the memory. Instead, the LLC is divided into **cache sets**, each covering a fixed subset of the memory space. Each of these cache sets contains several **cache lines**. For example, the Intel Core i7-3720QM processor, which belongs

to the Haswell family, includes  $8192 = 2^{13}$  cache sets, each of which can hold 12 lines of  $64 = 2^6$  bytes each, giving a total cache size of 8192x12x64=6MB. When the CPU needs to check whether a given physical address is present in the L3 cache, it calculates which cache set is responsible for this address, then only checks the cache lines corresponding to this set. As a consequence, a cache miss event for a physical address can result in the eviction of only one of the relatively small amount of lines sharing its cache set, a fact of which we make great use in our attack. The method of mapping between 64-bit physical addresses and 13-bit cache set indices has been reverse engineered by Hund et al. in 2013 [12]: of the 64 physical address bits, bits 5 to 0 are ignored, bits 16 to 6 are taken directly as the lower 11 bits of the set index, and bits 63 to 17 are hashed to form the upper 2 bits of the cache index. The LLC is shared between all cores, threads, processes, users, and even virtual machines running on a certain CPU chip, regardless of privilege rings or other protection similar mechanisms.

Modern personal computers use a virtual memory mechanism, in which user processes do not typically have direct knowledge or access to the system's physical memory. Instead, these processes are allocated virtual memory pages. When a virtual memory page is accessed by a currently executing process, the operating system dynamically associates the page with a page frame in physical memory. The CPU's memory management unit (MMU) is in charge of mapping between the virtual memory accesses made by different processes and accesses to physical memory. The size of pages and page frames in most Intel processors is typically set to 4KB, and both pages and page frames are page aligned - the starting address of each page is a multiple of the page size. This means that the lower 12 bits of any virtual address and its corresponding virtual address are generally identical, another fact we use in our attack.

#### 1.2 Cache Attacks

The cache attack is the most well-known representative of the general class of micro-architectural attacks, which are defined by Aciii¿œmez in his excellent survey [2] as attacks which "exploit deeper processor ingredients below the trust architecture boundary" to recover secrets from various secure systems. Cache attacks make use of the fact that, regardless of higher-level security mechanisms such as sandboxing, virtual memory, privilege rings, hypervisors etc., both secure and insecure processes can interact through their shared use of the cache. This allows an attacker to craft a "spy" process which can measure and make inferences about the internal state of a secure process through their shared use of the cache. First identified by Hu in 1992 [11], several results have

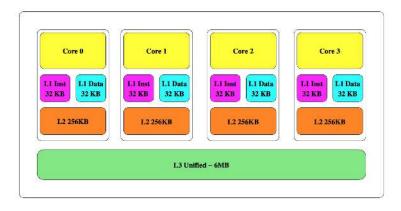


Figure 1: The Intel Ivy Bridge Cache Architecture (taken from [22])

shown how the cache side-channel can be used to recover AES keys [17, 4], RSA keys [19], and even allow one virtual machine to compromise another virtual machine running on the same host [20].

Our attack is modeled after the PRIME+PROBE attack method, first described by Osvik et al. in [17] in the context of the L1 cache. The attack was later extended by Yarom et al. in [23] to last-level caches on systems with large pages enabled, and we extend it in this work to last-level caches in the more common case of 4K-sized pages. In general, the PRIME+PROBE attack follows a four-step pattern. In the first step, the attacker creates one or more eviction sets. An eviction set is a set of locations in memory which, when accessed, can take over a single cache line which is also used by the victim process. In the second step, the attacker primes the cache set by accessing the eviction set. This forces the eviction of the victim's code or instructions from the cache set and brings it to a known state. In the third step, the attacker triggers or simply waits for the victim to execute and potentially utilize the cache. Finally, the attacker probes the cache set by accessing the eviction set yet again. A low access latency suggests that the attacker's code or data is still in the cache, while a higher access latency suggests that the victim's code made use of the cache set, thereby teaching the attacker about the victim's internal state. The actual timing measurement is carried out by using the unprivileged assembler instruction RDTSC, which provides a very sensitive measurement of the processor's cycle count. Iterating over the linked list also serves a secondary purpose by forcing the cache set yet again into an attacker-controlled state, thus preparing for the next round of measurements.

#### 1.3 The Web Runtime Environment

Javascript is a dynamically typed, object-based scripting language with runtime evaluation, which powers the

client side of the modern web. Javascript code is delivered to the browser runtime in source-code form and is compiled and optimized by the browser using a just-in-time mechanism. The fierce competition between different browser vendors resulted in an intense focus on improving Javascript performance. As a result, Javascript code performs in some scenarios on a level which is on par with that of native code.

The core functionality of the Javascript language is defined by the ECMA industry association in Standard ECMA-262 [7]. The language standard is complemented by a large set of application programming interfaces (APIs) defined by the World Wide Web Consortium [6], which make the language practical for developing web content. The Javascript API set is constantly evolving, and browser vendors add support to new APIs over time according to their own development schedules. Two specific APIs which are of use to us in this work are the Typed Array Specification [9], which allows efficient access to unstructured binary data, and the High Resolution Time API [16], which provides sub-millisecond time measurements to Javascript programs. As we show in Subsection 5.1, a large majority of Web browsers in use today support both of these APIs.

Javascript code runs in a highly **sandboxed** environment – code delivered via Javascript has highly restricted access to the system. For example, Javascript code cannot open files, even for reading, without the permission of the user. Javascript code cannot execute native language code or load native code libraries. Most significantly, Javascript code has **no notion of pointers**. Thus, it is impossible to determine even the virtual address of a Javascript variable.

# 1.4 Our Contribution

Our objective was to craft a last-level cache attack which can be deployed over the web. This process is quite challenging since Javascript code cannot load shared libraries or execute native language programs, and since Javascript code is forced to make timing measurements using scripting language function calls instead of using dedicated assembler instruction calls. These challenges notwithstanding, we have been able to successfully extend cache attacks to the web-based environment:

- We present a novel method of creating a non-canonical eviction set for the last-level cache. In contrast to [23], our method does not require the system to be configured for large page support, and as such can immediately be applied to a wider variety of desktop and server systems. We show that our method runs in a practical time even when implemented in Javascript.
- We present a fully functional last-level cache attack using unprivileged Javascript code. We evaluate its performance using a covert channel method, both between different processes running on the same machine and between a VM client and its host. The nominal capacity of the Javascript-based channel is on the order of hundreds of kilobits per second, comparable to that of the native code approach of [23].
- We show how cache-based methods can be used to
  effectively track the behavior of the user. This application of cache attacks is more relevant to our attack model than the cryptanalytic applications often
  explored in other works.
- Finally, we describe possible countermeasures to our attack and discuss their systemwide cost.

**Document Structure:** In Section 2 we presents the design and implementation of the different steps of our attack methodology. In Section 3 we present a covert channel constructed using our attack methodology and evaluate its performance. In Section 4 we investigate the use of cache-based attacks for tracking user behavior both inside and outside the browser. Finally, Section 5 concludes the paper with a discussion of countermeasures and open research challenges.

# 2 Attack Methodology

As described in the previous section, the four steps involved in a successful PRIME+PROBE attack are: creating an eviction set for one or more relevant cache sets, priming the cache set, triggering the victim operation and finally probing the cache set again. While the actual priming and probing are pretty straightforward to implement, finding cache sets which correlate to interesting system behaviors and creating eviction sets for them is

less trivial. In this Section we describe how each of these steps was implemented in Javascript.

# 2.1 Creating an Eviction Set

# 2.1.1 Design

As stated in [23], the first step of a PRIME+PROBE attack is to create an eviction set for a certain desired cache set shared with a victim process. This eviction set consists of a set of variables which are all mapped by the CPU into the same cache set. The use of a linked list is meant to defeat the CPU's memory prefetching and pipelining optimizations, as suggested by [20]. We first show how we create an eviction set for an arbitrary cache set, and later address the problem of finding which cache set is shared with the victim.

As discussed in [17], the L1 cache determines the set assignment for a variable based the lower bits of its virtual address. Since the attacker is assumed to know the virtual addresses of its own variables, it was thus straightforward to create an eviction set in the L1 attack model. In contrast, set assignments for variables in the LLC are made by reference to their physical memory address, which are not generally available to an unprivileged process. The authors of [23] partially circumvented this problem by assuming that the system is operating in large page mode, in which the lower 21 bits of the physical and virtual addresses are identical, and by the additional use of an iterative algorithm to resolve the unknown upper (slice) bits of the cache set index.

In the attack model we consider, the system is running in the traditional 4K page mode, where only the lower 12 bits of the physical and virtual addresses are identical. To our further difficulty, Javascript has no notion of pointers, so even the virtual addresses of our own variables are unknown to us.

The mapping of 64-bit physical memory addresses into 13-bit cache set indices was investigated by Hund et al. in [12]. They discovered that accessing a contiguous 8MB "eviction buffer" of physical memory will completely invalidate all cache sets in the L3 cache. While we could not allocate such an eviction buffer in usermode (indeed, the work of [12] was assisted by a kernelmode driver), we allocated an 8MB byte array in virtual memory using Javascript (which was assigned by the operating system into an arbitrary and non-contiguous set of 4K physical memory pages), and measured the system-wide effects of iterating over this buffer. We discovered that access latencies to unrelated variables in memory were slowed down by a noticeable amount when we accessed them immediately after iterating through this eviction buffer. We also discovered that the slowdown effect persisted even if we did not access the entire buffer, but rather accessed it in offsets of once per every 64 bytes. However, it was not immediately clear how to map each of the 131K offsets we accessed inside this eviction buffer into each of the 8192 possible cache sets, since we did not know the physical memory locations of the various pages of our buffer.

A naive approach to solving this problem would be to fix an arbitrary "victim" address in memory, then find by brute force which set of 12 out of the 131K offsets share a set with this address. To do so, we could fix some subset of the 131K offsets, then measure whether the access latency to this victim address is increased after iterating through these offsets. If the latency increases, this means the subset contains the 12 addresses sharing the set with the victim address. If the latency does not change, then the subset does not contain at least one of these 12 addresses, allowing the victim address to remain in the cache. By repeating this process 8192 times, each time with a different victim address, we would be able to identify each cache set and create our data structure.

An immediate application of this heuristic would take an impractically long time to run. Fortunately, the page frame size of the Intel MMU, as described in Subsection 1.1, could be used to our great advantage. Since virtual memory is page aligned, the lower 12 bits of each virtual memory address are identical to the lower 12 bits of each physical memory address. According to Hund et al., 6 of these 12 bits are used in uniquely determining the cache set index. Thus, an offset in our eviction buffer cannot be the same cache set as all 131K other offsets, but rather only with the 8K other offsets sharing address bits 12 to 6. In addition, discovering a single cache set can immediately teach us about 63 additional cache sets located in the same page frame. Joined with the discovery that Javascript allocates large data buffers along page frame boundaries, this led to the greedy algorithm described in Algorithm 1.

By running Algorithm 1 multiple times, we can gradually create eviction sets covering most of the cache, except for those parts which are accessed by the Javascript runtime itself. We note that, in contrast to the eviction sets created by the algorithm of [23], our eviction set is **non-canonical** – since Javascript has no notion of pointers, we cannot identify which of the CPU's cache sets corresponds to any particular eviction set we discover. Furthermore, running the algorithm multiple times on the same system will result in a different mapping each time it is run. This property stems from the use of traditional 4K pages instead of large 2MB pages, and will hold even if the eviction sets are created using native code and not Javascript.

# Algorithm 1 Profiling a cache set

Let *S* be the set of unmapped pages, and address *x* be an arbitrary page-aligned address in memory

# 1. Repeat *k* times:

- (a) Iteratively access all members of S
- (b) Measure  $t_1$ , the time it takes to access x
- (c) Select a random page s from S and remove it
- (d) Iteratively access all members of  $S \setminus s$
- (e) Measure  $t_2$ , the time it takes to access x
- (f) If removing page s caused the memory access to speed up considerably (i.e.,  $t_1 t_2 > thres$ ), then this page is part of the same set as x. Place it back into S.
- (g) If removing page *s* did not cause memory access to speed up considerably, then this address is not part of the same set as *x*.
- 2. If |S| = 12, return S. Otherwise report failure.

#### 2.1.2 Evaluation

We implemented Algorithm 1 in Javascript and evaluated it on Intel machines using CPUs from the Ivy Bridge, Sandy Bridge and Haswell families, running the latest versions of Safari and Firefox on Mac OS Yosemite and Ubuntu 14.04 LTS, respectively. The systems were not configured to use large pages, but instead were running with the default 4K page size. The code snippet shown in Listing 1 shows lines 1.d and 1.e of the algorithm, and demonstrate how we iterate over the linked list and measure latencies using Javascript. The algorithm requires some additional steps to run under Chrome and under Internet Explorer, which we describe in Subsection 5.1.

Figure 2 shows the performance of the profiling algorithm, as evaluated on an Intel i7-3720QM running Firefox 35.0.1 for Mac OS 10.10.2. We were pleased to find that the algorithm was able to map more than 25% of the cache in under 30 seconds of operation, and more than 50% of the cache after 1 minute. The algorithm seems very simple to parallelize, since most of the execution time is spent on data structure maintenance and only a minority of it is actually spent in the actual invalidate-and-measure portion. The entire algorithm fits into less than 500 lines of Javascript code.

To verify that our algorithm was indeed capable of identifying cache sets, we designed an experiment that compares the access latencies for a flushed and an unflushed variable. Figure 3 shows two probability distribution functions comparing of the time required to access

```
0.6
                                               Probability density
                                                 0.5
// Invalidate the cache set
                                                 0.4
var currentEntry = startAddress;
                                                 0.3
do {
       currentEntry
                                                 0.2
     probeView.getUint32(currentEntry);
  while (currentEntry
                              startAddress);
                                                 0.1
   Measure access time
                                                   0
                                                    0
                                                            50
                                                                     100
                                                                              150
var
    startTime
                                                             Access Latency (ns)
  window.performance.now();
currentEntry =
```

0.7

primeView.getUint32(variableToAccesFigure 3: Probability distribution of access times for var endTime = window.performance.now(b)ushed vs. un-flushed variable (Haswell CPU)

Listing 1: Javascript code to invalidate a cache set, then measure access time

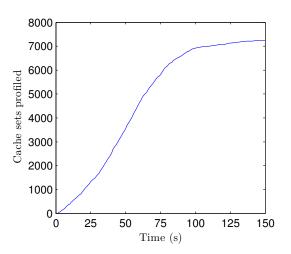


Figure 2: Cumulative performance of the profiling algorithm

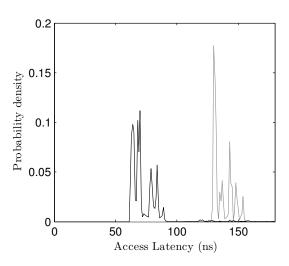


Figure 4: Probability distribution of access times for flushed vs. un-flushed variable (Sandy Bridge CPU)

a variable which has recently been flushed from the cache using our method (gray line) with the time required to access a variable which currently resides in the cache set (black line). The timing measurements were carried out using Javascript's high resolution timer, and thus include the additional delay imposed by the Javascript runtime. It is clear to see that the two distributions are distinguishable, confirming the correct operation of our profiling method. Figure 4 shows a similar plot captured on an older-generation Sandy Bridge CPU, which includes 16 entries per cache set.

By selecting a group of cache sets and repeatedly measuring their access latencies over time, the attacker is provided with a very detailed picture of the real-time activity of the cache. We call the visual representation of this image a "memorygram", since it is looks quite similar to an audio spectrogram.

A sample memorygram, collected over an idle period of 400ms, is presented in Figure 5. The X axis corresponds to time, while the Y axis corresponds to different cache sets. The sample shown has a temporal resolution of 250µs and monitors total of 128 cache sets. The intensity of each pixel corresponds to the access latency of this particular cache set at this particular time, with black representing a low latency, indicating no other process accessed this cache set between the previous measurement and this one, and white representing a higher latency, suggesting that the attacker's data was evicted from the cache between this measurement and the previous one.

Observing this memorygram can provide several immediate insights. First, it is clear to see that despite the use of Javascript timers instead of machine language instructions, measurement jitter is quite low active and inactive sets are clearly differentiated. It is also easy to notice several vertical line segments in the memorygram, indicating multiple adjacent cache sets which were all active during the same time period. Since consecutive cache sets (within the same page frame) correspond to consecutive addresses in physical memory, we believe this signal indicates the execution of a function call which spans more than 64 bytes of assembler instructions. Several smaller groups of cache sets are also accessed together. We theorize that the these smaller groups correspond to variable accesses. Finally, the white horizontal line indicates a variable which is constantly accessed during our measurements. This variable probably belongs to the measurement code or to the underlying Javascript runtime. It is remarkable that such a wealth of information about the system is available to an unprivileged webpage!

# 2.2 Identifying Interesting Regions in the Cache

The eviction set allows the attacker to monitor the activity of arbitrary sets of the cache. Since the eviction set we receive is non-canonical, the attacker must now correlate the cache sets he has profiled to data or code locations belonging to the victim. This learning/classification problem was addressed earlier by Zhang et al. in [25] and by Yarom et al. in [23], where various machine learning methods such as SVM were used to derive meaning from the output of cache latency measurements.

To effectively carry out the learning step, the attacker needs to induce the victim to perform an action, then examine which cache sets were touched by this action, as formally defined in Algorithm 2.

Finding a function for step (c) of the algorithm was

# **Algorithm 2** Interesting Regions in the Cache

Let  $S_i$  be the data structure matched to eviction set i

#### 1. For each set *i*:

- (a) Iteratively access all members of  $S_i$  to prime the cache set
- (b) Measure the time it takes to iteratively access all members of  $S_i$
- (c) Perform an interesting operation
- (d) Measure once more the time it takes to iteratively access all members of  $S_i$
- (e) If performing the interesting operation caused the access time to slow down considerably, then the operation was associated with cache set *i*.

actually quite challenging due to the limited permissions granted to Javascript code. This can be contrasted with the ability of Apecechea et al. to trigger a minimal kernel operation by invoking an empty sysenter call [3]. To carry out this step, we had to survey the Javascript runtime to discover function calls which may trigger interesting behavior, such as file access, network access, memory allocation, etc. We were also interested in functions which take a relatively short time to run and left no background "tails" such as garbage collection which would impact our measurement in step (d). Several such functions were discovered in a different context by Ho et al. in [10]. Another approach would be to induce the user to perform an interesting behavior (such as pressing a key on his keyboard) on the behalf of the attacker. The learning process in this case might be structured (where the attacker knows exactly when the victim operation was executed), or unstructured (where the attacker can only assume that relatively busy periods of system activity are due to victim operations. We make use of both of these approaches in the attack we present in Section 4.

Since our code will always detect activity caused by the Javascript runtime, the high performance timer code, and other components of the web browser which are running regardless of the call being executed, we actually called two similar functions and examined the **difference** between the activity profile of the two evaluations to identify relevant cache sets.

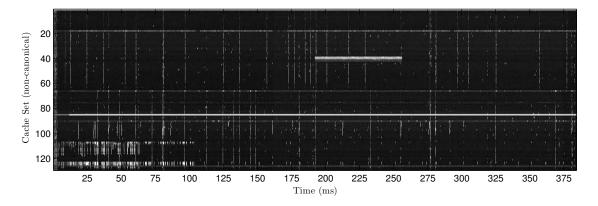


Figure 5: Sample memorygram

# 3 A Cache-Based Covert Channel in Javascript

# 3.1 Motivation

As shown in [23], last-level cache access patterns can be used to construct a high-bandwidth covert channel and effectively exfiltrate sensitive information between virtual machines co-resident on the same physical host. In our particular attack model, in which the attacker is not in a co-resident virtual machine but rather inside a webpage, the motivation for a covert channel is different but still very interesting.

By way of motivation, let us assume that a Security Agency is tracking the criminal mastermind Bob. Making use of a spear phishing campaign, the Agency installs a piece of software of its own choosing, commonly referred to as an Advanced Persistent Threat (APT), on Bob's personal computer. The APT is designed to log incriminating information about Bob and send it to the Agency's secret servers. Bob is however highly security-savvy, and is using an operation system which enforces strict Information Flow Tracking [24]. This operating system feature prevents the APT from accessing the network after it accesses any file containing private user data.

Javascript-based cache attacks can immediately be put to use to allow the Agency to operate in such a scenario, as long as Bob can be enticed to view a website controlled by the Security Agency. Instead of transmitting the private user data over the network, the APT will use the cache side-channel to communicate with the malicious website, without setting off the flow tracking capabilities of the operating system.

This case study is inspired by the "RF retro-reflector" design attributed to a certain Security Agency, in which a collection device such as a microphone does not transmit the collected signal directly, but instead modulates the

collected signal onto an "illuminating signal" sent to it by an external "collection device".

#### 3.1.1 Design

The design of our covert channel system was influenced by two requirements: first, we wanted the transmitter part to be as simple as possible, and in particular we did not want it to carry out the eviction set algorithm of Subsection 2.1. Second, since the receiver's eviction set is non-canonical, it should be as simple as possible for the receiver to search for the sets onto which the transmitter was modulating its signal.

To satisfy these requirements, our transmitter/APT simply allocates a 4K array in its own memory and continuously modulates the collected data into the pattern of memory accesses to this array. There are 64 cache sets covered by this 4K array, allowing the APT to transmit 64 bits per time period. To make sure the memory accesses are easily located by the receiver, the same access pattern is repeated in several additional copies of the array. Thus, a considerable percentage of the cache is actually exercised by the transmitter, in contrast to the method of [23] which assumes a canonical eviction set, and thus only activates two lines.

The receiver code profiles the system's physical memory, then searches for one of the page frames containing the data modulated by the APT. The data can then be demodulated from the memory access pattern and uploaded back to the server, all without violating the information flow tracking protections.

# 3.1.2 Evaluation

Our attacker model assumes that the transmitter part is written in (relatively fast) native language, while the receiver part is implemented in Javascript. Thus, we assumed that the limiting factor in the performance of our system is the sampling speed of the malicious website.

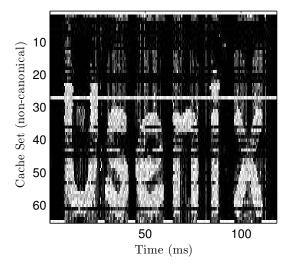


Figure 6: A host-to-host covert channel

To evaluate the bandwidth of this covert channel, we wrote a simple program that iterates over memory in a predetermined pattern (in our case, a bitmap containing the word "Usenix"). Next, we attempted to search for this memory access pattern using a Javascript cache attack, then measured the maximum sampling frequency at which the Javascript code could be run.

Figure 6 shows a memorygram capturing an execution of this covert channel. The nominal bandwidth of the covert channel was measured to be approximately 320kbps, a figure which compares well with the 1.2Mbps bandwidth achieved by the native code cross-VM covert channel implemented by [23].

Figure 7 shows a similar memorygram where the receiver code is not running directly on the host, but rather on a virtual machine (Firefox 34 running on Ubuntu 14.01 inside VMWare Fusion 7.1.0). While the peak bandwidth of the in this scenario was severely degraded to approximately 8kbps, the fact that a webpage running inside a virtual machine is capable of probing the underlying hardware is still quite surprising.

# 4 User Behavior Tracking Through Cache Attacks

Most works which evaluate cache attacks assume that the attacker and the victim share a colocated machine inside a cloud-provider data center. Such a machine is not typically configured to accept interactive input, and accordingly most works in this field focus on the recovery of cryptographic keys or other secret state elements, such as random number generator states [26]. For this work, we chose to examine how cache attacks can be used to track the interactive behavior of the user, a threat which

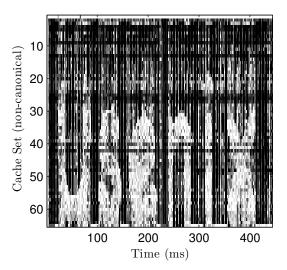


Figure 7: A host-to-VM covert channel

is more relevant to the attack model we consider. We note that [20] have already attempted to track keystroke timing events using coarse-grained measurements of system load on the L1 cache.

This case study shows how a malicious webpage can track a user's activity using a cache attack. In the attack presented below, we assume that the user has loaded a malicious webpage in a background tab or window, and is carrying out sensitive operations in another tab, or even in a completely different application with no Internet connectivity.

We chose to focus on mouse and network activity because the operating system code that handles them is non-negligible. Thus, we expected them to have a relatively large cache footprint. They are also easily triggered by content running within the restricted Javascript security model, as we describe below.

# 4.1 Design

The structure of both attacks is similar. First, the profiling phase is carried out, allowing the attacker to probe individual cache sets using Javascript. Next, during a training phase, the activity to be detected (i.e. network activity or mouse activity) is triggered, and the cache activity is sampled multiple times with a very high temporal resolution. While the network activity was triggered directly by the measurement script (by executing a network request), we simply waved the mouse around over the webpage during the training period <sup>1</sup>.

By comparing the cache activity during the idle and active periods of the training phase, the attacker learns

<sup>&</sup>lt;sup>1</sup>In a full attack, the user can be entited to move the mouse by having him play a game or fill out a form.

which cache sets are uniquely active during the relevant activity and trains a classifier on these cache sets. Finally, during the classification phase, the attacker monitors the interesting cache sets over time to learn about the user's activity.

We used a basic unstructured training process, assuming that the most intensive operation performed by the system during the training phase would be the one being measured. To take advantage of this property, we calculated the Hamming weight of each measurement over time (equivalent to the count of cache sets which are active during a certain time period), then applied a k-means clustering of these Hamming weights to divide the measurements into several clusters. We then calculated the mean access latency of each cache set in every cluster, arriving at a *centroid* for each cluster. To classify an unknown measurement vector, we measured the Euclidean distance between this vector and each of these centroids, classifying it as the closest one.

In the classification phase, we generated network traffic using the command-line tool wget and moved the mouse outside of the browser window. To provide ground truth for the network activity scenario, we concurrently measured the traffic on the system using tepdump, then mapped the timestamps logged by tepdump to the times detected by our classifier. To provide ground truth for the mouse activity scenario, we wrote a webpage that timestamps and logs all mouse events, then moved the mouse over this webpage. We stress that the mouse-logging webpage was run on a different browser (Chrome) than the measuring code (Firefox).

# 4.2 Evaluation

The results of the activity measurement are shown in Figures 8 and 9. The top part of both figures shows the real-time activity of a subset of the cache. On the bottom part of each figure are the classifier outputs, together with the ground truth which was collected externally. As the Figures show, our extremely simple classifier was quite capable of detecting mouse and network activity. The performance of the attack can be improved without a doubt by using more advanced training and classification techniques. We stress that the mouse activity detector did not detect network activity, and vice versa.

The classifier's measurement rate was only 500Hz. As a result, it could not count individual packets but rather periods of network activity and inactivity. In contrast, our mouse detection code actually logged more events than the ground truth collection code. This is due to the fact that the Chrome browser throttles mouse events to web pages down to a rate of approximately 60Hz.

Detecting network activity can be a stepping stone toward a deeper insight of the user's activity, as famously

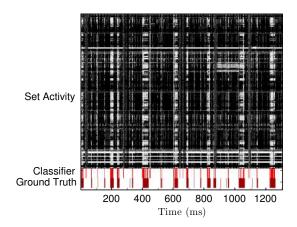


Figure 8: Network activity detection

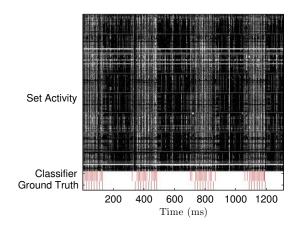


Figure 9: Mouse activity detection

demonstrated by Chen et al. in [5]. In essence, while Chen et al. assumed a network-level attacker which can monitor all incoming and outgoing traffic to the victim, the techniques presented here can enable any malicious website to monitor the concurrent web activities of its users. The attack can be bolstered by more indicators, such as memory allocations (as explored by [13]), DOM layout events, disk writes and so on.

### 5 Discussion

This work shows that side-channel attacks have a much wider reach than previously expected. Instead of being relevant only for very specific attacker scenarios, the attack proposed here can be mounted against most computers connected to the Internet. The fact that so many systems are suddenly vulnerable to side-channel attacks suggests that side-channel resistant algorithms and systems should be the norm, rather than the exception.

# **5.1** Prevalence of Vulnerable Systems

Our attack requires a personal computer powered by an Intel CPU based on the Sandy Bridge, Ivy Bridge, Haswell or Broadwell micro-architectures. According to data from IDC, more than 80% of all PCs sold after 2011 satisfy this requirement. We furthermore assume that the user is using a web browser which supports the HTML 5 High Resolution Time API and the Typed Arrays specification. Table 1 notes the earliest version at which these APIs are supported for each of the common browser brands, as well as the proportion of global Internet traffic coming from vulnerable browser versions, according to StatCounter GlobalStats measurements as of January 2015 [1]. As the table shows, more than 80% of desktop browsers in use today are vulnerable to the attack we describe.

The effectiveness of our attack depends on being able to perform precise measurements using the Javascript High Resolution Time API. While the W3C recommendation of this API [16] specifies that the a high-resolution timestamp should be "a number of milliseconds accurate to a thousandth of a millisecond", the maximum resolution of this value is not specified, and indeed varies between browser versions and operating systems. In our testing we discovered, for instance, that the actual resolution of this timestamp for Safari for MacOS was on the order of nanoseconds, while Internet Explorer for Windows had a  $0.8\mu s$  resolution. Chrome, on the other hand, offered a uniform resolution of  $1\mu$  on all operating systems we tested.

Since, as shown in Figure 3, the timing difference between a single cache hit and a single cache miss is on the order of 50ns, the profiling and measurement algorithms need to be slightly modified to support systems with coarser-grained timing resolution. In the profiling stage, instead of measuring a single cache miss we repeat the memory access cycle multiple times to amplify the time difference. For the measurement stage, we cannot amplify a single cache miss, but we can take advantage of the fact that code access typically invalidates multiple consecutive cache sets from the same page frame. As long as at least 20 out of the 64 cache sets in a single page frame register a cache miss, our attack is successful even with microsecond time resolution.

The attack we propose is also easily applied to mobile devices such as smartphones and tablets. It should be noted that the Android Browser supports High Resolution Time and Typed Arrays starting from version 4.4, but at the time of writing the most recent version of iOS Safari (8.1) did not support the High Resolution Time API.

# **5.2** Countermeasures

The attacks described in this report are possible because of a confluence of design and implementation decisions starting at the micro-architectural level and ending at the Javascript runtime: The method of mapping a physical memory address to cache set; the inclusive cache micro-architecture; Javascript's high-speed memory access and high-resolution timer; and finally, Javascript's permission model. Mitigation steps can be applied at each of these junctions, but each will impose a drawback on the benign uses of the system.

On the micro-architectural level, changes to the way physical memory addresses are mapped to cache lines will severely confound our attack, which makes great use the fact that 6 of the lower 12 bits of the address are used directly to select a cache set. Similarly, the move to an exclusive cache micro-architecture, instead of an inclusive one, will make it impossible for our code to trivially evict entries from the L1 cache, making measurement much more difficult. These two design decisions, however, were chosen deliberately to make the CPU more efficient in its design and in its use of cache memory, and changing them will exact a performance cost on many other applications. In addition, modifying a CPU's micro-architecture is far from trivial, and definitely impossible as an upgrade to already deployed hardware.

On the **Javascript** level, it seems that somewhat reducing the resolution of the high-resolution timer will make this attack more difficult to launch. However, the high-resolution timer was created to address a real need of Javascript developers for applications ranging from music and games to augmented reality and telemedicine.

Browser brand	High Resolution Time Support	Typed Arrays Support	Worldwide prevalence
Internet Explorer	10	11	11.77%
Safari	8	6	1.86%
Chrome	$20^{2}$	7	50.53%
Firefox	15	4	17.67%
Opera	15	12.1	1.2%
Total	_	_	83.03%

Table 1: Prevalence of vulnerable desktop browsers, according to [1]

A possible stopgap measure would be to restrict access to this timer to applications which gain the user's consent (for example, by displaying a confirmation window) or the approval of some third party (for example, by being downloaded from a trusted "app store").

An interesting approach could be the use of heuristic profiling to detect and prevent this specific kind of attack. Just like the abundance of arithmetic and bitwise instructions was used by Wang et al. to indicate the existence of cryptographic primitives [21], it can be noted that the various measurement steps of our attack access memory in a very particular pattern. Since modern Javascript runtimes already scrutinize the runtime performance of code as part of their profile-guided optimization mechanisms, it should be possible for the Javascript runtime to detect profiling-like behavior from executing code and then modify its response accordingly (for example by jittering the high-resolution timer, dynamically moving arrays around in memory, etc).

# 5.3 Conclusion

In this report, we showed how the micro-architectural side-channel attack, which is already recognized as an extremely potent attack method, can be effectively launched from an untrusted web page. Instead of the traditional cryptanalytic application of the cache attack, we instead showed how user behavior can be effectively tracked using this method. The potential reach of side-channel attacks has been extended, meaning that additional classes of secure systems must be designed with side-channel countermeasures in mind.

# Acknowledgements

We are thankful to Henry Wong for his investigation of the Ivy Bridge cache replacement policy and to Burton Rosenberg for his tutorial about pages and page frames.

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