Hardware-Assisted Application Misbehavior Detection

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Abstract. *Programming is an error-prone task, which may result in application misbehavior. From the safety point of view, crashes are undesirable as they affect user experience, whereas from the security point of view, vulnerability exploitation can lead to security violations. Although fuzzing and other testing techniques help to minimize undesirable events, they do not eliminate them. As an additional "protection" layer, real-time monitoring can help in handling cases of previously unaddressed violations. However, approaches like Control Flow Integrity (CFI) are too specific to be extended to the general case. To overcome this challenge, we propose a hardware-assisted flow learning technique able to profile and detect deviations from the standard behavior, thus ensuring proper application execution.*

1. Introduction

Humans are prone to fail, which extends to our developed programs. An study [DHS 2013] shows that 90% of security incidents are due to software defects. In addition, the OWASP project classifies buggy implementation as the root cause of most Web attacks [Morana 2010]. When systems are exploited, the impact of implementation flaws ranges from operational issues [Guardian 2015] to financial [Register 2011] and privacy [Forbes 2017] losses. To reduce the number of application bugs, good software engineering is essential [DoD 2005]. In this field, fuzzy testing is noticeable for its ability to test program paths [Li et al. 2017].

Despite all efforts, application misbehavior still appears in practice, as we can observe in the number of exploited applications [Kaspersky 2017]. To handle those cases in actual scenarios, runtime monitoring approaches have been proposed, such as CFI policies to counter Return-Oriented-Programming (ROP) attacks [Pappas et al. 2013]. However, policy-based approaches present many drawbacks, such as requiring recompilation [Tice et al. 2014] and granularity issues [Göktaş et al. 2014]. In addition, this kind of policy is attack-specific, thus not handling other kind of flow changes. As adopting specific policies for each attack class is impractical, there is a need for developing more general solutions.

As an alternative approach, we propose a learning solution that profiles successful application executions to build a baseline of integer control flow paths and compares it to further executions to identify misbehavior cases. Such learning characteristic allows us to detect attacks without writing specific monitoring rules.

To evaluate our proposal, we have implemented a prototype solution that performs real-time data collection and analysis. Our solution was implemented upon a hardware-based framework [Botacin et al. 2018], thus allowing Commercial-Off-The-Shelf (COTS) binaries inspection without recompilation. In addition, collecting data at hardware level reduces the overall imposed performance overhead of continuous system monitoring. We have evaluated our prototype both with synthetic and real-world applications and showed its effectiveness. In addition, we discuss how our proposal could be leveraged to enhance existing operating systems to enrich crash reports.

The remainder of this paper work is organized as follows: In Section 2, we present related work and how our solution differs from these; in Section 3, we introduce our proposal key concepts; in Section 4, we discuss our solution design and implementation; in Section 5, we evaluate our solution with synthetic and real applications, showing its effectiveness; in Section 6, we discuss the advances and limitations presented by our proposed concept; finally, we draw our conclusions in Section 7.

2. Related Work

Our proposed solution relates to multiple research topics, each one presented below to better position our work among related solutions.

Fuzzing. Fuzzing solutions try to maximize the coverage of the possible execution paths of a given binary code [Li et al. 2017, Pham et al. 2016, Böhme et al. 2016]. Our solution relates to fuzzing ones in the sense that our learning step also tries to cover multiple paths. However, we do not try to generate inputs to reach each code branch, but we rely on user interactions to do so. By runtime monitoring typical application executions, our solution is able to learn the most frequently taken branches, thus identifying when an abnormal one is taken, which might indicate an exploitation path.

Control Flow Integrity (CFI). CFI policies are popular solutions to mitigate ROP attacks. They enforce, for instance, that `RET` instructions must be preceded by `CALL` ones, thus mitigating the effects of the execution of code injected via buffer overflow exploitation. Solutions such as Kbouncer [Pappas et al. 2013] and ROPecker [Cheng et al. 2014] are able to runtime monitor code execution and detect the violation of this flow integrity policy. Our solution is related to CFI policies in the sense that we try to detect abnormal execution paths. However, we do not rely on specific rules, such as the `CALL-RET` one, but we infer implicit rules from a learning-based technique.

Branch Monitoring. Branch monitors are hardware features able to provide information about the executed branch instructions with low overhead. Their usage goes from application profiling [Akiyama and Hirofuchi 2017] and coverage testing [Shye et al. 2005] to security [Botacin et al. 2018]. In this work, we rely on branch monitors to track application executions with low performance penalty. Branch information is used as input to our learning mechanism to decide whether taking a given path is allowed or not.

Hardware-Assisted approaches. The development of hardware extensions to handle security problems is a growing field. In the literature, we can find a wide range of proposals, from real-time Control Flow Graph (CFG) checking [Arora et al. 2005] to syscall clustering [Das et al. 2016]. The closest related work to ours is presented in [Zhang et al. 2004], on which authors modify a processor to detect flow transitions which violate given policies. In this work, we propose to implement a similar concept but using an existing hardware feature instead, the processor branch monitor. The rationale behind hardware-assisted approaches is to avoid performance degradation, therefore, most proposals opt to move all processing components to hardware. In our understanding, the major drawback regarding software solutions is data capture, not threat intelligence, thus we propose moving only this first step to the hardware. In this sense, our work is related to [Ozsoy et al. 2015], which proposes a two level monitor, notifying other system components—such as an antivirus (AV)—when a violation is detected.

3. Concepts & Solution proposal

Computer programs can be seem as Finite State Machines (FSMs), in which states are transitioned based on the inputted data until reaching the final state, thus outputting the computation result, as illustrated by Figure 1. If the state machine (program) is not well modelled or implemented, undesired transitions can lead to unexpected states, which correspond to bugs.

In memory, computer programs are organized as sequences of instructions. Each instruction block is responsible to change the current program state. The order that the instructions are executed defines the output result. In the FSM analogy, branch instructions are the transition functions, as shown in Figure 2. Therefore, monitoring them allows us to understand which states the program is leaving and entering.

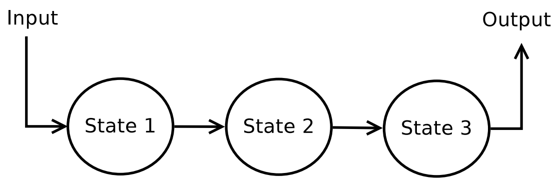


Figure 1. Program as a Finite State Machine. Data is inputted to an initial state and transitions lead to the final state, outputting the computation result.

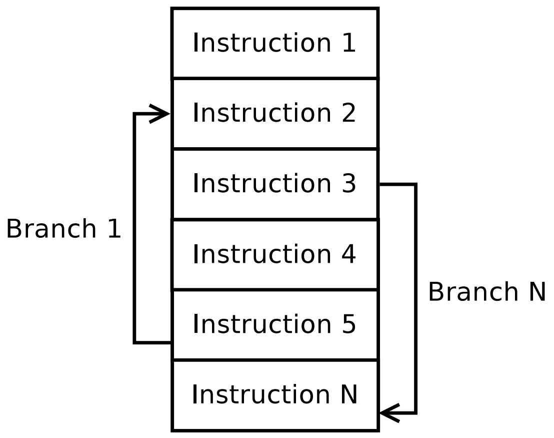


Figure 2. Program representation in memory. Branch instructions are responsible for state transitions.

When a program is executing a given task (opening a file, for instance), its state machine traverses a given path, represented by branches. In a general way, always that the same task is performed, the same path is traversed, thus the same branches are executed. Therefore, if a sequence of known branches is succeeded by unknown ones, the program is probably misbehaving—which may be related to an identified bug or even to an exploitation attempt. If we were able to know which are the usually executed branches and runtime check the executed ones, we would be able to detect application misbehavior events in runtime. In this work, we present a monitoring mechanism and a learning solution for this task.

To implement such solution, we propose a two-phase mechanism: In the first step, a profiling phase, our solution learns which are the allowed branches; In the second step, the matching phase, our solution monitors the taken branches and matches them against the database of allowed branches previously learned, as shown in Figure 3. When a violation is detected, a warning is raised.

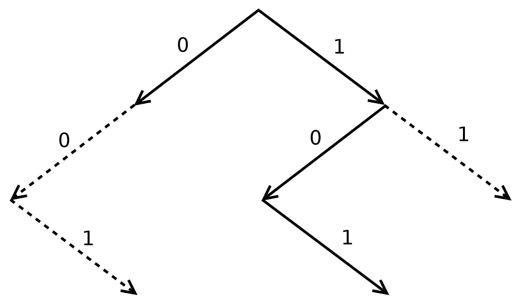


Figure 3. Expected Branches Policy. The solid arrows correspond to paths previously seem, thus representing expected branches. The dotted arrows represent so-far unknown branches, which might indicate a misbehavior.

In practice, this proposal presents a significant challenge: Despite taking almost the same branches while performing the same task, the taken paths are data-dependent. `IF-ELSE` constructions for odd/even values, for instance, may lead to distinct intermediary paths. Our proposal to tackle these cases is to rely on user interactions to achieve good code coverage. The hypothesis behind this decision is that the users will have exercised the most common paths after some time and that the same paths will continuously be executed in the future. We consider this hypothesis as reasonable as, in fact, most programs often execute the same set of instructions (hot code regions), such as loops [Gordon-Ross and Vahid 2003].

Therefore, as both the training phase as well as the matching one consist on monitoring taken branches during user interaction, we can build an unified framework, differing only on the applied policy (learning or matching), which makes the solution more flexible. Once a violation is detected, our solution notifies an upper instance about its occurrence. Such upper instance can be an AV solution or an OS subsystem. In our proposal, we have implemented our own AV-analogous application as an userland component.

For the sake of evaluation, we implemented an intelligence model able to apply two distinct policies: i) On the strict model, any unexpected branch is considered as a flow violation. Whereas very effective, this mode requires huge efforts regarding training to increase the coverage and thus not generate false positives; ii) On the more flexible policy, we do not look to single branches, but a series of them, by relying on a moving window. It allows relaxing the training requirements while still detecting flow violations—ROP payloads, for instance, are composed by a sequence of gadgets terminated by branches (`RET`) [Göktaş et al. 2014]. On both policies, the misbehaving program is terminated when the violation is detected. The number of unexpected branches within a given window to define the execution as a flow violation is given by a configurable threshold. A threshold of 1 would turn the solution back to the strict mode.

Both presented policies rely on a non-supervised, automated learning procedure to learn the allowed branches. A more relaxed policy could be implemented by adding user interaction to the system: When a violation occurs, the user could be prompted to decide whether the process should be terminated or the taken branches are due to a new valid behavior. In this case, the solution would add the so-far unknown branches to the database, which would convert our solution on a semi-supervised approach.

4. Implementation

In this section, we present implementation details regarding the monitoring solution as well as the learning mechanism.

4.1. Data collection

To collect data from the processor branch monitor, we relied on an branch-based framework [Botacin et al. 2018]. We have set the solution to monitor only the code image section from the target binaries, filtering them by their Process IDentifiers (PIDs).

As our running operating system is Address Space Layout Randomization (ASLR)-enabled, branches from distinct executions are not directly comparable, as base addresses differ. To allow the comparison, we implemented an address normalization procedure, discarding branch base addresses and considering only their offsets inside the code images. The offset values are unique for each binary regardless of distinct executions. The effect of such procedure is shown in Table 1.

Table 1. ASLR-aware data collection. Offset normalization. Despite the distinct image base addresses, branch offsets are unique.

Branch	Execution 1	Execution 2	Execution N	Offset
I	0x7FF1D30	0x7FF3D30	0x7FF5D80	0x1D30
II	0x7FF1E30	0x7FF3E30	0x7FF5E80	0x1E30
II	0x7FF1EF0	0x7FF3EF0	0x7FF5F40	0x1EF0

4.2. Automated Learning Approach

As the branch-based framework is able to provide us with all required branch information, we need only to collect data from a given path (source and target addresses) and store them on a database of allowed branches. For each taken branch address, we store their immediate successors, on a multi-level hash structure, as shown in the Figure 4. The hash-based indexing allows us to check whether a given branch is expected in O(1) at the same time we do not have to worry about repeated entries.

Figure 5 shows an example of the training procedure in action while learning the allowed paths from Code 1. The `zero` (0) flag indicates that the first taken branches were unknown—as the database was not previously populated—thus causing the system to learn. In the second time the same addresses were identified, the system already had such data in the database, as shown by the `hit` (1) flag.

4.3. Detection

In the detection phase, branches are sampled on a moving window way. For each taken branch within a given moving window, the next allowed branches are looked for in the

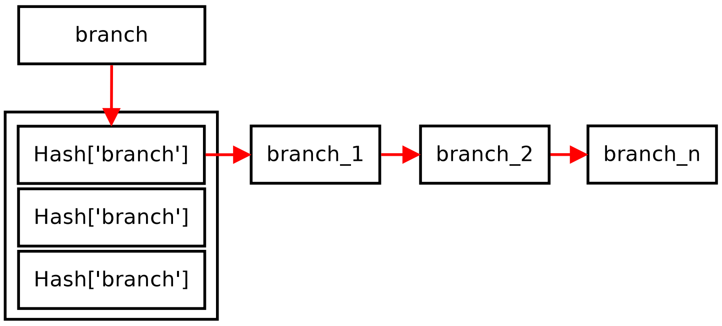
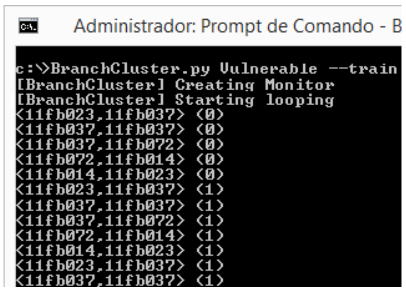


Figure 4. Branch Database. Source addresses are used to index allowed target addresses. Unidentified entries are considered as unexpected branches.



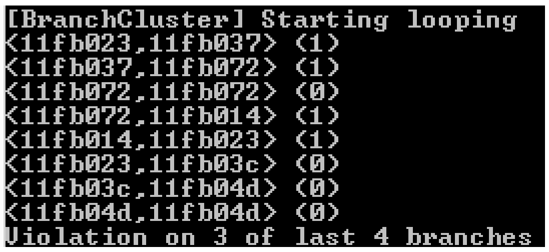
```
c:\>BranchCluster.py Vulnerable --train
[BranchCluster] Creating Monitor
[BranchCluster] Starting looping
<11fb023,11fb037> (0)
<11fb037,11fb037> (0)
<11fb037,11fb072> (0)
<11fb072,11fb014> (0)
<11fb014,11fb023> (0)
<11fb023,11fb037> (1)
<11fb037,11fb037> (1)
<11fb037,11fb072> (1)
<11fb072,11fb014> (1)
<11fb014,11fb023> (1)
<11fb023,11fb037> (1)
<11fb037,11fb037> (1)
```

Figure 5. Automated learning. Flags 1 and 0 indicate, respectively, whether a given branch was expected (allowed) to occur or not.

database. If the following branch instruction is found, the `allowed` flag is set. Otherwise, the `not_allowed` flag is set. This procedure is repeated for all instructions within the current window. The ratio of `not_allowed` over `allowed` branches is compared against a threshold (according the considered policy), thus leading to the misbehavior conclusion in case of a high score. Figure 6 shows the detection window of a given branch violation.

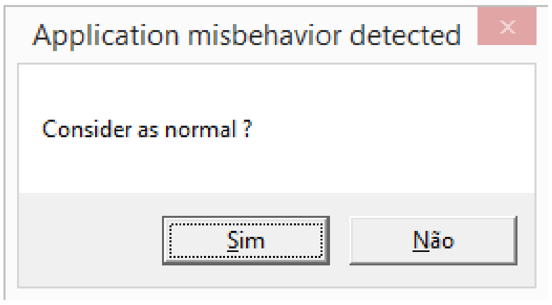
4.4. Semi-Supervised Learning Approach

This approach can be considered as an extension of the detection mechanism. However, when a violation is identified, the monitored program is not immediately terminated, but the user is prompted to decide which action will be taken. If the user specifies the unexpected branches are allowed, the solution adds them to the database. The next time these branches were executed, they will be considered as expected, thus not triggering warnings anymore. Figure 7 shows the solution asking user to validate a given violation detection as a true violation.



```
[BranchCluster] Starting looping
<11fb023,11fb037> (1)
<11fb037,11fb072> (1)
<11fb072,11fb072> (0)
<11fb072,11fb014> (1)
<11fb014,11fb023> (1)
<11fb023,11fb03c> (0)
<11fb03c,11fb04d> (0)
<11fb04d,11fb04d> (0)
Violation on 3 of last 4 branches
```

Figure 6. Misbehavior Detection. Solution detects violations using a threshold value over data from a moving window.



Application misbehavior detected

Consider as normal ?

Figure 7. Semi-supervised learning. Solution asks for user confirmation.

5. Evaluation

In this section, we evaluate our solution's proper working. We first validate it with a synthetic example to demonstrate its correctness. Secondly, we evaluate its use against a real world exploit, demonstrating its application on practical scenarios.

5.1. Validation

To validate our proposal, we developed the synthetic example presented in Code 1:

```
main(){
  char string[MAX_STRING];
  int loop=0;
  int opt=0;
  do{
    scanf("%d",&opt);
    if (opt>0){
      printf("Greater␣than␣zero\n");
    }else if(opt<0){
      printf("Smaller␣than␣zero\n");
    }else{
      printf("Bad␣choice\n");
      // An string overflow here
      // changes the loop control variable
      scanf("%s",string);
    }
  }while(!loop);
  printf("Should␣never␣be␣executed\n");
```

Code 1. Validation code. It presents three distinct paths. The latter also presents an overflow vulnerability which allows the execution of a so-far unreachable code.

This code presents 3 main decision paths:

1. Input values greater than zero trigger the first `printf` as they follow only the first path and return to the loop.
2. Input values smaller than zero trigger the second `printf` as they follow only the second path and return to the loop.
3. The zero value triggers the third path, which fills the buffer with an user-supplied string. There is a clear buffer overflow regarding the `scanf` statement, as the string is allocated in the stack right before the `loop` control variable. Overflowing such variable would flip `loop` bits, causing execution to exit the loop, thus calling the last `printf`, which should had never be executed.

Our evaluation consisted in the following steps: i) training the solution for the paths 1 and 2; ii) running the solution with the trained dataset and ensure both trained paths are properly flagged as allowed; iii) exercise the third path, with no overflow, which should trigger the supervised learning, as this path was not trained in the last step. iv) Consider the violation as legitimate execution, thus forcing the solution to add the new branches to the database; v) exercise the same path, without triggering detection, because the solution learned this path as allowed in the last step; vi) Exercise the third path with overflow, thus triggering the detection mechanism; vii) finally, flag execution as a violation, forcing application to quit. Our solution has proven to be able to pass all described tests.

5.2. Real Application

We also evaluated our solution effectiveness on a real scenario. To do so, we launched a real ROP attack, based on a known exploit [Knaps 2015], against a real-world application (Easy File Share). After the learning step, the software was monitored while being exploited. The identified unexpected branches are shown in Code 2.

```
Unexpected Branches: [0x150C, 0x1C80C, 0x13020]
Unexpected Branches: []
Unexpected Branches: [0x1731A, 0xD31A, 0x7C81A, 0x33B1A, 0x2AC1A, 0
    xFC21A, 0x12941A, 0x29A1A]
```

Code 2. Real application under a ROP-based attack. Differences between the expected and the observed branches.

We notice that while some branches sources were succeeded by the same branch targets than in the training step, thus triggering an empty difference set, some branches were followed by unexpected ones, showing our solution's ability to detect abnormal behavior in real scenarios.

5.2.1. Enriching Crash Reports

In addition to enabling real time detection, the presented experiment suggested our solution can also be used in other contexts. Inspired by BranchTrace [Willems et al. 2012], we believe crash reports can be enriched by including branch data. As an example, consider the execution of the vulnerable file sharing application as presented above. At a given point, the branch window present the following consecutive target branches: `0x34A3 (1)` and `0x6fB8 (0)`. This means that the first branch target was expected whereas the second was an unexpected branch resulting from the execution of the previous code block, as well as its predecessor branches. If such information were submitted to the application developers, it could help them to find the bug cause in an easier way, because the buggy construction is probably located around the unexpected branch. In fact, by disassembling the code surrounding these branches, we identified the following pieces of code, as shown in Figure 8.

The legitimate call starts executing at `line 1`. This function body is responsible for manipulating the stack and then calling a function pointed by the `ecx` register (`line 12`), previously loaded from the stack (`line 11`). As this branch leads to an unexpected target, it suggests the stack may have been corrupted. The call target code pops a value from the stack and returns (`lines 13-15`). The execution jumps to an unknown location (`line 16`), followed by a `nop sled` (`line 17`), until reaching another code portion (`line 17`). In fact, by knowing the exploit, we can verify that the stack was effectively corrupted: the `POP-POP-RET` sequence is a ROP-like gadget, followed by the usual `JMP` to the payload, which aligns itself through `NOP`s, until reaching the malicious shellcode.

5.3. Overhead

In addition to effective, we must ensure our developed solution does not impose significant overhead penalty, so the original application keeps running well. From the data capture point of view, as our solution is based on a branch monitor framework, our solution's overhead is bounded by the performance penalty imposed by it (20%, on average). We highlight, however, that the framework was originally set to use a small interrupt threshold of a single instruction, which increases performance penalty. We can reduce the

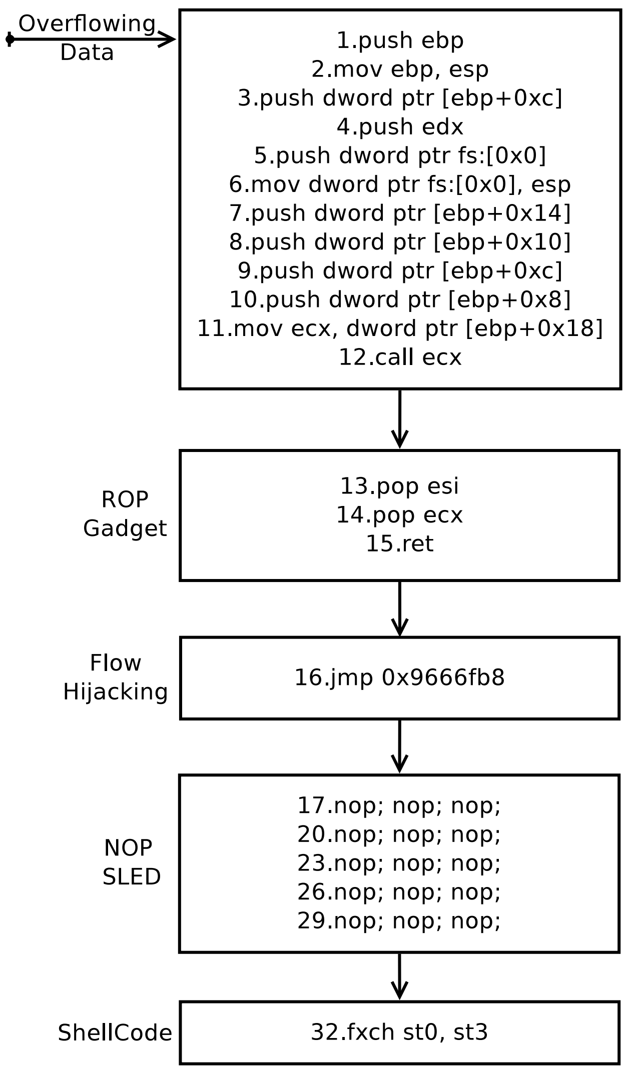


Figure 8. Exploit Execution. After a buffer overflow, the stack holds user-injected addresses which are used to redirect the flow to a malicious code portion acting as a shellcode-analogous.

performance penalty by using a larger interrupt threshold, as we do not need branch-by-branch execution support.

In practice, our measurements indicate that the overhead is application and context-dependent, as each one presents a distinct rate of taken branches. A high-branch-density application will be more interrupted than an I/O-bound application, for instance. In our tests, the `vulnerable` test program presented the lowest overhead footprint, as all their branches fit on a single OS page. On the other hand, the `Chrome` browser execution is severely affected, because each newly opened tab creates a new system process, thus executing a huge amount of branches.

We also observed distinct performance penalty impacts according the core the monitored application is running. OS schedulers often cause the CPU core 0 to present higher loads whereas the other cores present lower ones. When running in a heavy-loaded core, such as core 0, the overhead is increased, because our solution has to filter out much more data—we remark that the framework captures data in a system-wide way. On the other hand, the solution presents smaller overheads when running in the other processor cores.

6. Discussion and Future Work

In this section, we discuss the impact of our proposed solution and how it could be integrated into real, practical systems.

6.1. Advances, Implications & Limitations

The presented solution is our first attempt to solve the misbehavior detection problem by using hardware assistance. It enables us to perform the task without significant performance penalty, which is a hard-to-achieve requirement for this security solution class.

We showed that our solution is feasible on real cases and that the presented development implicates on an increased bug detection capabilities on many branch-monitor-equipped systems. Moreover, as it is based on a hardware-feature, it is able to monitor COTS binaries, without requiring code instrumentation and/or modification. We believe this is a significant contribution towards increased bug detection.

As a short-term limitation, the branch monitor framework is limited to collect data on a system-wide manner, thus imposing the overhead of monitoring all running processes (which are further filtered in software). This limitation can be overcome by using emerging hardware features, such as the Intel's Processor Tracer (PT) [R. 2013].

In the long-term, we believe that the major challenge that such kind of approach is subject to is the solution's capability to decide whether a given misbehavior is derived from an exploit or from an ordinary bug. Such information is critical to perform real time threat detection in a more complete way. Such development is beyond implementation constraints as it is also limited by theoretical aspects.

6.2. OS self-monitoring proposal

Our presented evaluation showed that our solution is able to identify application misbehaviors without any prior written rules. Although the results are preliminary, we believe that many systems and applications could benefit from using such kind of approach.

As an example, we suggest using our approach for OS self-monitoring. Currently, modern operating systems already collect telemetry data [ZDNet 2016] from running applications. These systems could also be extended to monitor applications executions, profile them and detect abnormal behaviors, as we proposed.

In addition to detection, systems could also be able to launch automatic remediation procedures, such as automatic backup recovery or some other system configuration restore, when a misbehavior were detected.

Even on unrecoverable cases, the profiled data could be sent to application maintainers as part of bug and/or crash reports, enriching the existing fault data collection mechanisms, so that developers would be able to more precisely identify which instruction block triggered the faulting behavior.

6.3. Usage Scenarios and Policies

Our proposed solution is suitable to operate on distinct scenarios. As an example, its permanent, real-time capabilities make it a candidate to monitor critical systems, where faults must be immediately identified.

In addition, we believe there is a real demanding field regarding the monitoring of recently installed applications, third-party software components and unpatched systems. Our system could be launched by the OS, for instance, when a new application is installed, thus starting the profiling step. After some time monitoring the application without any significant occurrence, the mechanism could be turned off.

6.4. A Cooperative Learning Model

Our solution relies on user interaction to learn the allowed branches. On the one hand, it covers most of exercised behavior by a given user, regardless of the usage pattern. On the other hand, rare but legitimate paths may be not learned if not previously exercised.

Whereas user-based coverage may be enough for most cases, some scenarios may require a really increased branch coverage. Therefore, more branches should be exercised, thus making our approach closer to the fuzzing ones. However, as we intend to provide an alternative to these, it is not reasonable to generate multiple random inputs to exercise our solution. Thus, an alternative approach must be developed.

A way of achieving high coverage is to perform a distributed learning procedure, clustering the branches taken on multiple machines. It could be implemented by regularly sending the newly learned branches to a remote repository and downloading new allowed paths definitions, as an next-generation AV definition update.

We believe that such kind of implementation is more more feasible for immediate application in a mobile software ecosystem, because their application stores already update applications' configurations based on performance data [Google].

6.5. Future Work

As future work, we will extend our framework in two ways: i) by investigating new, additional hardware features which could enable us to profile applications and establish an execution baseline without significant performance impact; and ii) by extending our threat intelligence component to perform more complex matches. Machine-learning solutions could be used, for instance, to predict whether given unexpected branches constitute a violation or not.

7. Conclusions

In this paper, we presented a hardware-assisted, branch learning solution able to detect application misbehavior by comparing a given branch trace to a learned profile. We evaluated the proposed solution with conceptual and real applications demonstrating its ability to handle buggy and exploitable software. We also discussed the conceptual application of such solution as an Operating System built-in feature.

The code of all presented examples and of our developed detector is available at `https://github.com/marcusbotacin/BranchMonitoringProject/tree/master/Misbehavior.Detection`.

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