Binary Debloating for Security via Demand Driven Loading

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Abstract

Modern software systems heavily use C/C++ based libraries. Because of the weak memory model of C/C++, libraries may suffer from vulnerabilities which can expose the applications to potential attacks. For example, a very large number of return oriented programming gadgets exist in glibc that allow stitching together semantically valid but malicious Turing-complete programs. In spite of significant advances in attack detection and mitigation, full defense is unrealistic against an ever-growing set of possibilities for generating such malicious programs.

In this work, we create a defense mechanism by debloating libraries to reduce the dynamic functions linked so that the possibilities of constructing malicious programs diminishes significantly. The key idea is to locate each library call site within an application, and in each case to load only the set of library functions that will be used at that call site. This approach of demand-driven loading relies on an input-aware oracle that predicts a near-exact set of library functions needed at a given call site during the execution. The predicted functions are loaded just in time, and the complete call chain (of function bodies) inside the library is purged after returning from the library call back into the application. We present a decision-tree based predictor, which acts as an oracle, and an optimized runtime system, which works directly with library binaries like GNU libc and libstdc++.

We show that on average, the proposed scheme cuts the exposed code surface of libraries by 97.2%, reduces ROP gadgets present in linked libraries by 97.9%, achieves a prediction accuracy in most cases of at least 97%, and adds a small runtime overhead of 18% on all libraries (16% for glibc, 2% for others) across all benchmarks of SPEC 2006, suggesting this scheme is practical.

1 Introduction

Modern software relies heavily on libraries that are often built for supporting a large amount of functionality. In a given application, however, only a small of amount of such functionality may get used. For example, programmers leverage Android libraries, lean on machine learning and AI tools, and build on top of web frameworks to improve productivity [3, 9, 19, 42, 53]. Although these frameworks can be dauntingly large, it is normal to use only a small subset of the APIs and in fact a small subset of their functionality. A recent study [46] shows that only about 10% of the shared library functions in userspace programs that ship with Ubuntu Desktop 16.04 are used. For performance reasons, these underlying libraries are inevitably written in C/C++. The memory model offered by C/C++ suffers from many weaknesses and leads to a large number of exploits that expose the applications or frameworks that use the libraries, in turn leaving them vulnerable. One such library that forms the core of C/C++ libraries and applications is the GNU version of libc, or “glibc” [23]. Glibc also acts as a basic building block of other libraries and their higher-level APIs in GNU/Linux systems. Unfortunately, the list of vulnerabilities and exploits in glibc keeps growing, with 99 known and published vulnerabilities at the time of this writing [13], of which nine were published in 2018.

Over the years, several hardware and software defense mechanisms have been developed to detect and mitigate the attacks; however, such mechanisms have limitations. Some of the hardening techniques such as address-space layout randomization [44] (ASLR) and data execution prevention [2] (DEP) cannot protect against advanced control-flow hijack techniques like return-oriented programming [48] (ROP) and jump-oriented programming [7] (JOP). To defend against the exploitation of these advanced vulnerabilities, specific and general mechanisms have been invented. One such well-known defense mechanism that has been researched extensively is control-flow integrity (CFI) [1, 6, 12, 26, 36, 61], a mechanism that attempts to restrict the program execution to legal paths only.

While coarse-grained CFI such as bin-CFI (a binary-level CFI technique) [63] restricts jumps to ROP and JOP gadgets at addresses other than that of functions, it over-approximates the legal execution paths possible through calls and returns.
This allows for malicious program paths and thus overlooks certain attacks. To reduce the approximation of the allowed set of calls from a call site and to maintain legal returns, a number of fine-grained CFI techniques such as πCFI [41] and MCFI [40] leverage the source code of libraries. However, computing a fully-precise CFI is an intractable problem because of the inherent limitations in pointer analysis [19], irregular control flow in the presence of setjmp and longjmp, or an inherent inability to distinguish between a legal and illegal dynamic control flow base with regard to the current program input. µCFI leverages Intel Processor Trace and static analysis to enforce its unique target code property [26] for indirect control-flow transfers. It differs from our proposed solution in several ways, including: it relies on Intel PT (which currently requires kernel support); it handles application code and not libraries; it requires source; and it is limited against certain classes of attacks (as we will show below in a code example).

Control-Flow Bending [10] (CFB) showed that even a fully-precise static CFI cannot defend against many non-control data attacks. CFB demonstrated that with the availability of a dispatcher function, commonly available in glibc, a CFI mechanism can be fooled to successfully carry out an attack. CFI also does not handle non-control data attacks such as certain types of privilege escalation [11, 64]. Unlike CFI, which allows memory corruption but prevents exploits, another class of defense mechanism that prevents memory corruption is memory safety that requires checks to verify the correctness of memory operations. While memory safety techniques can thwart almost all control-flow hijack attacks they incur overheads ≥ 2x [38]. Because CFI in general does not completely defend against all the control-hijack attacks for which it is built, it should be complemented with defense mechanisms for specific attacks. Moreover, as defenses strengthen, new attacks are revealed that undermine the current best practices of defense mechanisms. Due to the sophistication of attack construction tools, the number of newly discovered attacks are growing at a much faster rate, which might lead to a losing battle [54].

To reduce the effects of such unseen attacks, a promising way forward is program debloating [31], that is, downsizing the amount of code available for constructing an attack gadget. One of the established ways of accomplishing this is software debloating, in which unwanted or dead code is removed from the application or library. Current compiler-based link-time optimizations statically determine a set of functions to be removed from the linked library using a combined analysis of unreachable functions, global constant propagation, and interprocedural evaluation of branch outcomes using the fixed points of unreachable code and (conditionally propagated) constants [15, 29, 51, 52]. Piece-wise compilation [46] collects address-taken functions of each module and loads only those functions that are required by the program. However, many functions are still stitched to the program, so it still relies on a CFI mechanism for defense. Such approaches retain a conservative over-approximation of the set of functions that are linked and needed by the program as a whole. That is, at different program points, multiple functions of the library could be reachable/needed, so they are left linked; This significantly increases the code surface (of dynamically linked functions). ROP and JOP gadgets across call sites are still available for exploitation in the code that is linked to the application.

Software debloating at call sites that use function pointers faces the same limitation of over-approximation seen in CFI, allowing construction of such gadgets. Although static program debloating is a right step towards thwarting unknown possibilities of attacks, it is quite ineffective due to the limitations of static analyzability of programs, because of which a lot of code still remains linked. A major limitation of the static debloaters is that the attacker can replay the execution of a statically debloated code over and over under the guidance of a debugger to systematically construct a Turing-complete attack gadget. Also, most of the state-of-the-art defense techniques in CFI, memory safety, and software debloating require source code analysis, thus leaving out libraries such as glibc that are notorious for extremely complex control flow which poses a huge obstacle for inter-procedural analysis of reasonable sophistication (static or dynamic).

In response to the limitations mentioned above, we propose BlankIt, a defense mechanism based on binaries of the libraries that significantly reduces dynamically linked functions, adds protection against ROP and JOP attacks, and overcomes the limitations of false negative approximation in CFI and significantly diminishes attackers’ ability to carry out replay to devise a new attack gadget. BlankIt relies on the following core ideas:

- Only load a set of needed/predicted functions from the library at a call site on demand at runtime. The predictor acts as an input-based oracle and provides a list of such functions required. These functions are loaded in a protected read-only area. The other functions in the library are blanked out either by writing zeros or the semantic equivalent of a NOP.

- The execution of the loaded library functions continues under the supervision of probes, which fire before each function’s invocation; if more functions are needed for execution, they are loaded on demand under the guidance of an audit and alarm phase.

- When the library execution returns to the call site, the complete call chain of loaded functions is purged or blanked out.

- On misprediction, a simultaneously running process receives the arguments to the library function to run with full memory safety and check for violations.

The above scheme significantly diminishes an attacker’s ability to create a gadget that transcends the set of functions
The success of the blanking scheme depends on predicting the exact set of functions needed at runtime. Over approximation expands dynamically linked functions (e.g. leaving more ROP gadgets intact), whereas under approximation increases runtime overheads. BlankIt prediction is highly precise, relying on machine learning to determine the input-related dynamic execution path in an oracular manner. The learning technique overcomes the limitations of over-approximation that exist in the case of fine-grained CFI mechanisms like πCFI or MCFI. For example, in the general case like that of Code 1 any fine-grained CFI mechanism or software-debloating mechanism like piece-wise compilation [46] fails to see that myFnPtr always calls function foo when argc is greater than 2 and classifies both foo and bar as valid jumps from the function pointer call. In contrast, our prediction mechanism, based on profiling several call characteristics, learns that foo is called by myFnPtr when argc is greater than 2. Under perfect prediction or oracular behavior (which we will show is achievable), BlankIt does not allow bar to be loaded. If mispredictions may occur and are allowed, then BlankIt will not load bar without entering a audit and alarm phase that checks for violations. Similarly, handling the valid set of jumps in the case of setjmp/longjmp is very easy in BlankIt compared to CFI mechanisms.

Code pointer Integrity (CPI) [28] is a defense mechanism that uses memory safety only on pointers that can directly or indirectly modify code pointers (control-flow) thus lowering the overheads of a full memory safety mechanism but allowing some control-flow bending attacks. For example, in the non-control data attack from [64] shown in Code 2 the user is verified by an input password, and the result is assigned to the variable "user". The user is frequently checked to provide access to certain operations. However, between the checks, the function interacts with the user to get some other inputs. Input "someinput" can be manipulated by the user, causing a buffer overflow vulnerability in line 12, and leading to super user access. This attack is not handled by CPI or the latest CFI (πCFI, μCFI), but in the case of BlankIt, the "call_super_user" function is not predicted, and the attack is detected in the audit and mitigation phase that checks for violations (please refer to section 5.5 for details). However, BlankIt only handles such attacks when a function call is involved, since that is the prediction granularity it currently operates on. On top of flagging such attacks, another advantage is that BlankIt is a binary defense mechanism and works on glibc, unlike most of the state-of-the-art defense mechanisms like CPI, πCFI, or CET.

Code 1: Snippet for considering CFI and BlankIt approaches

```c
1 void foo(int M, int N)
2 {
3     for (int i = 0; i < N; i++)
4         A[i] = A[i-1] + A[i-2];
5     }
6
7 int a = 0, b = 0;
8     if (argc > 2) {
9         myFnPtr = &foo;
10    }
11    a = 1; b = 2;
12 }
13
14 int call_normal_user();
15
16 }
```

Code 2: Attack missed in CPI and πCFI but caught in BlankIt

For successful deployment of this technique, the prediction accuracy must be very high, and for SPEC CPU 2006 benchmarks our technique achieves an average prediction accuracy of over 94% (100% on 3 benchmarks, and over 97% for 9 benchmarks). BlankIt on average reduces the number of dynamically linked functions by over 97% and reduces ROP gadgets in the code section by over 97%. BlankIt incurs a small overhead of 18% on SPEC 2006 with all libraries.

1.1 Contributions

The following are the contributions of this work:
1. A framework for dynamically loading and unloading library functions on demand at binary level.

2. A prediction mechanism for predicting the required library functions to be loaded at each call-site, thus avoid over-approximation (such as in CFI).

3. An audit and alarm technique that on misprediction runs a full-blown memory safety check on the library function to catch any attack.

4. An evaluation of our framework using specCPU2006 benchmarks and its supporting libraries—glibc, libm, libgcc, and libstdc++—some of which are are not handled in mechanisms that depend on library source.

Our contributions result in the following security implications:

1. The set of active dynamically linked functions is reduced to protect against future, unforeseen exploits that mainly rely on code reuse and replay-based attack construction, and we provide reasonable metrics and results for the same.

2. The glibc library, notorious for vulnerabilities and not tackled by most of the state-of-the-art defense techniques, is addressed.

3. Safety guarantees for known exploits that state-of-the-art CFI techniques cannot provide (as seen in the function pointer example in Code 1, or the example case study in section 6).

4. Some of the control-flow bending attacks that depend on non-control data are thwarted, which falls under the area of attacks deemed as outside the scope of CFI and also CPI.

## 2 BlankIt Overall Framework

BlankIt is an environment for demand driven loading of library functions at runtime. BlankIt first creates a dynamic environment for demand-driven loading when the library is initially imported. Then during runtime it loads library functions on demand. When the library is imported, BlankIt does the following for every function: inserts a probe at the function entry, copies the function code after the probe into a safe read-only memory, and wipes (blanks) out all the code after the inserted probe.

The application itself is also instrumented beforehand. A predictor (a decision tree learnt through off-line profiling), is instrumented at various points in the program’s control flow graph prior to each library call site. Its output at runtime is simply the chain of functions within the library that it expects to occur at a given call site. Different artifacts are included in the decision tree, such as the call site ID, reverse dominance frontier (RDF), and the arguments to the library function. When the application calls a library function, the probe (inserted when the library was imported) gets invoked. This probe checks if the functions called are as predicted, and if they are, execution continues inside loaded functions. If, however, the call is not through legitimate means (non-predicted and not legal) then an attack is detected. Any attempts to bypass the probe results in a fault or crash because the code section has been blanked. Finally, when the control returns to the application, the functions that were copied are reset back to zero. This purging is what minimizes dynamically linked functions.

The defense of BlankIt at a higher level is depicted in Figure 1. It shows that in the normal runtime A, an overflow vulnerability can be exploited to jump to an arbitrary address within glibc, but in runtime B with BlankIt, since the library functions are wiped out, jumping to an arbitrary address results in a fault. The prediction mechanism reduces the set of functions that can be reached through the vulnerability.

As mentioned, a highly accurate yet light-weight prediction framework is very critical to the success of BlankIt. The prediction framework first classifies call chains inside the linked library as divergent or non-divergent. This is based on the underlying call graphs. As much as 27% of the functions within glibc are found to exhibit linear control flow (i.e. all functions are must-reachable); these can be loaded without performing any dynamic prediction. The remaining functions (73%), however, must be dynamically predicted. The prediction models are built in a context-sensitive, deliberate manner during training runs. Not all context is considered. That is, generating a model that captures multiple features of a library call site’s context (such as preceding program paths, call chains, etc.) could provide high accuracy, but the elaborate model could also pose very high overheads. Instead, we compute the predicates on which the call site and call arguments are control dependent and generate the model solely based on that. More details on this are presented in the forthcoming
sections.

We empirically show (based on the intuition of static value separation via SSA) that a model based on reverse dominance frontiers is accurate and lightweight. Such an approach provides a highly likely subset of the may-reachable set of functions from a given call site and the subset itself is a function of arguments of the callsite summarized by the static-dynamic artifacts in the application. All of this together allows us to predict the may-reachable set of functions based on the calling context at each call site.

When a function that is not in the predicted set is invoked at runtime, it means either there was a misprediction or an attack. In the case of misprediction, the function was required but left blank. It can also happen, however, that a function is part of the predicted set but not actually needed. In this latter case, the execution continues without any glitches, but it exposes additional function surface. Overprediction, which is very rare, as shown later in Section 5 is still better than static approximation of reachable functions in CFI, as only valid call chains are loaded. In the case of underprediction, i.e. when functions are required but remain blanked, BlankIt starts an audit and alarm phase to check for an attack. In this phase the library function and its arguments are handed over to a process that runs the library function with a full memory safety mechanism under Valgrind [39], which then checks if the misprediction is an attack.

2.1 Threat Model

In our threat model, we assume that the program is not self-modifying, and an attacker can read/write the data section and read/execute the code section of a vulnerable program. We assume that the application source, LLVM compiler that all external libraries can be a source of threat, and any such artifacts in the application. All of this together allows us to predict the may-reachable set of functions based on the calling context at each call site.

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3 BlankIt Runtime

For demand-driven loading, we have developed BlankIt, a binary tool based on Intel’s Pin [43]. It wipes (blanks) out all functions in a library and loads (copies) them only on demand. The details of the design and optimization of BlankIt are described here. The runtime is guided by the predictor which is described in the next section.

3.1 BlankIt Design

BlankIt is a pintool and adheres to the programming model set forth by Pin. There are two modes in which Pin operates: JIT and Probe. JIT mode is flexible but slower; probe mode is limited but faster. Probe mode supports instrumentation at the start and end of functions, but not at instruction granularity. In probe mode, all the instrumentation is inserted at the start-up, and then execution is handed off to the application to run natively; thus, the overhead incurred is the probe insertion overhead at the beginning and the dynamic execution costs of executing probes. Since the instrumentation is static, there are no stalls during the execution, and an attacker cannot use this to his/her advantage. Due to these reasons, BlankIt uses probe mode. In terms of functionality, probe mode is sufficient for BlankIt, and in terms of overhead, it is necessary.

On-demand loading is achieved in BlankIt through two stages. The first is when a library is loaded initially for execution. The second is during execution of the application. At initialization time, BlankIt iterates over all of the executable’s shared objects. Then for each function within a shared object, it overwrites the first few bytes with a trampoline and sets the remaining bytes to zeros. In other words, once initialization is complete, every shared object’s text section has been wiped out and replaced with thunks. BlankIt maintains a separate copy of functions in a trusted cache. At runtime, the application normally calls into its library functions without any changes. The original functions now contain trampolines at their start, however, which bounce execution into a generic handler, or in Pin-speak, a probe. At this point, BlankIt has the responsibility of patching back the original code and transferring control accordingly. The BlankIt probe copies the original function’s bytes back into place (i.e. from the end of
the trampoline to the end of the function) and then returns to the function. This mechanism is illustrated below.

Figure 2 depicts this mechanism for a two-function call chain. When the application calls a library function (malloc in this case), execution proceeds along arrow 1 to the original function location in libc. During initialization, however, BlankIt had replaced it with a trampoline. The trampoline causes execution to flow along arrow 2 to the probe_copy function. Focusing first on lines 6-9, a loop over a map of copies and remembers all functions of the currently predicted set of functions. Here we see that malloc and mmap64 are needed, so they are copied back into place in libc. Arrows 4, 5, 6 and 7 are needed because in this example, malloc depends on mmap64 for this particular invocation.

A second type of probe (Figure 3) is used for both blanking and prediction. In a BlankIt-enabled application, prediction calls are hoisted before the library calls. The predictions are themselves library calls, though, and BlankIt simply replaces them with a probe during initialization.

In Figure 3, the application calls a library function (free), so at compile-time, a call to blankit_predict was inserted with an ID of the profiled/learned call chain at that call site. The initialization for BlankIt replaced all blankit_predict calls with probe_blankit_predict, which allows it to blank the last set of copied functions (lines 4-5) and update the ID of the new prediction set (line 6). probe_blankit_predict then returns along arrow 2 to the application, where it invokes the library function, free. At this point, the behavior is similar to that described in Figure 2.

3.2 BlankIt Optimizations

A number of optimization opportunities are available in runtime. We focus on just two of several that were implemented. Some optimizations were ineffective, as well. For example, prediction allows for the possibility of copying not only the missing bytes of a function back into place but also overwriting the trampoline, as well. The upshot of this is that there will be no trampoline overhead for subsequent calls in the predicted chain (i.e. arrows 5 and 6 in Figure 2). The potential downside is that the trampolines must be copied back when the blanking is done. There was no noticeable runtime difference with this change.

3.2.1 Lazy Blanking

Figure 3 depicts the second type of probe that is responsible for storing predictions and blanking the previous ones. As discussed, blanking does not happen at the return of every function call. Rather, it happens from within the next prediction call that occurs just before the first/entry call to a library. An alternative could be to blank at the return of every library call, but this has much more call overhead. More importantly, because blanking occurs when execution re-enters a library, there is a chance that the predicted functions are the same as the last predicted set. When this is the case, BlankIt does not need to blank anything. This kind of “lazy blanking” trades some security (by allowing the last call chain in the library to remain unblanked and exposed until the next library call) for speed; it still enforces security across call sites, though, since no two call chains remain linked to the application at the same time. Thus, this optimization does not have any adverse effect on attack surface or ROP gadgets as far as the library is concerned.

3.2.2 Full Call Chain Loading

BlankIt can be enabled to predict the entire sequence of calls within a library call from the application. This sequence will facilitate unblanking the next function and blanking the previous function in the call chain thus securing all functions in the library except for the current executing function. This will incapacitate any ROP or JOP attack within the call chain. Note that pin allows for calling a probe after every routine call during which the previous function is unblanked. However, by not blanking the previous function we expose the code within the loaded call chain. If an adversary would use any gadget within the loaded call chain its only a matter till the next jump to a function or blanked region is performed when the attack is caught. Any ROP within the call chain can also be caught by a shadow stack such as Intel’s CET [27]. As is reported later in Section 5, the number of maximum gadgets exposed at any library call advocates this optimization.
3.3 Audit and Alarm: Handling Misprediction

The drawback of any machine learning mechanism is that the deployment is not always 100% accurate. Such a reduction in accuracy results in false positives in BlankIt. However, when a mispredict occurs, BlankIt enters an audit and alarm phase, in which the library function arguments and the function name are passed on to an auditor process. The auditor loads the library through a dlopen call and calls the library function while executing with Valgrind [39], a complete memory safety mechanism. Further, BlankIt can choose to wait for its auditor to report an attack, or continue execution and let the auditor restore changes by the application, or kill the process. The choice depends on the process and the execution environment. For example, a virtual machine environment can easily restore the changes made by an application [62].

BlankIt also handles a few cases of non-control data attacks within the application other than the kind shown in Code 2. Please refer to the appendix section 9.2 for more details.

4 Call Graph Prediction

The BlankIt runtime is in some sense driven by the prediction part. The prediction is concerned with determining the expected, valid flow through the program. Distinguishing between (input-specific) legitimate dynamic control flow and an illegitimate counterpart is critical to thwarting attempts to construct a malicious security apparatus. A key goal of this work is to build such an oracle that takes into account input relatedness and predicts the functions that correspond to the legitimate control flow. As described earlier, the predictor guides the BlankIt runtime to dynamically load only the predicted functions while other functions are kept blank. We now describe how we construct such an oracle based on decision trees.

4.1 Overall Framework

1. First the static divergence analysis finds statically non-divergent functions for which no prediction is needed.

2. We then instrument the reverse dominance frontiers (RDFs) corresponding to every argument at every call site to construct a call context for the library call.

3. The instrumented application is then profiled, and the call context and argument values are logged along with the call chain.

4. This profile information is fed into a machine learning model that constructs a decision tree to predict the call chain depending on the call context.

5. The generated decision tree is then instrumented into the application at the application call site for prediction.

6. Finally, constant folding and dead code elimination is carried out to remove redundant predicates.

7. The instrumented application then feeds the predicted call chain into the BlankIt runtime system.

4.2 Static Call Flow Divergence Detection

In the first step of the prediction framework, we find library functions that don’t have statically divergent call flow. In other words, we identify functions in which the call sites do not reside in a different control flow path. If a library function is non-divergent, then all the dynamic calls of the function will result in the same call chain. We find non-divergent functions by checking if every call site within a function post dominates the entry block of the function as shown in Algorithm 1. If the callee is not on a control divergent path but is itself divergent, then the caller is also marked as a divergent function, and all other functions that call this function are also marked as divergent functions.
Algorithm 1 Static Divergence Detection

1: procedure NON-DIVERGENT(Function F)
2: \( BB_{entry} \leftarrow \) entry basic block in F
3: for each Call site \( C_i \):
4: \( fci \leftarrow \) function called in \( C_i \)
5: if non-divergent\((fci) \) && \( C_i \) postdominates \( BB_{entry} \) then
6: \( F \) is non-divergent
7: End for

In glibc, we found that among all the functions analyzed, roughly 27% of the functions are statically non-divergent. Such functions exhibit a constant single call-graph that can be statically determined for which no dynamic prediction is required; however, dynamic prediction is a must for the remaining 73% of call sites.

| Library   | #Divergent | #Non-divergent |
|-----------|------------|----------------|
| glibc-2.26| 1985       | 737            |

Table 1: Static divergence in glibc

4.3 Reverse Dominance Frontier-Based Prediction

After generating a database of statically non-divergent functions, we now look at predicting the call graph for the diverging ones. Normally, whole program path profiling would need instrumentation of every branch. This would result in a path prefix of a fixed window \( W \), entailing the context of the last \( W \) branches. This path prefix can then be used for prediction of the call chain within the function call. We leverage the fact that library functions are usually control divergent due to their arguments and contend that the static context required to predict the call chain is the control dependence of the arguments passed to the library.

This leads us to investigate the reverse dominance frontier (RDF) of the arguments of a call site, because the divergence in the library call path can be caused by the different definitions of arguments (determined by their respective RDF) reaching the call site. For example, in Figure 5, a library call to \( \text{libCall()} \) has one argument \( X_0 \), which is defined as the phi instruction of arguments \( X_1 \) and \( X_2 \). If the basic block \( B_2 \) is executed, \( X_0 \) has a negative value, but if the basic block \( B_3 \) is executed, \( X_0 \) has a positive value. In this case, both \( B_2 \) and \( B_3 \) are control dependent on \( B_1 \). Thus the branch condition at \( B_1 \) actually decides whether a positive or negative value is passed to \( \text{libCall()} \). If the execution path and the call chain within the \( \text{libCall()} \) function differs for positive and negative arguments, then we can learn to predict the call chain right after \( B_1 \). The intuition here is that the call chain inside a library call will be dependent on arguments sent to the library, which in turn could be statically separated into corresponding SSA variables of a backward slice and finally guarding control dependent branches.

With RDF based prediction, the context leading up to a call site consists of only the last executed RDF for every function argument. This minimal instrumentation has enough information to predict the call chain within a function with reasonable accuracy. The only extra instrumentation required is for correlating every branch with its corresponding function argument, and for each function argument to be instrumented with its RDF. When the profiling is done, the context for each call site is constructed separately, depending on the RDFs of its arguments. The instrumentation methodology is outlined in Algorithm 2.

4.4 Argument Value-Based Prediction

The control path in library functions can diverge because of the various values of the arguments that are reaching the call sites in the application from the same RDF. Since the RDF remains constant, RDF based prediction might not be sufficient. For example, we have observed that math library functions like \( \text{sqrt}(x) \) and \( \text{exp}(x) \) have different call chains depending on the range of the parameters. In order to handle such cases, we must classify the values of the function arguments that reach from a single RDF, so we capture the values of the arguments by profiling and appending the training model with the value. Once we have the data on which we want to learn and predict the behavior of the library call graph at each call site, we feed the data to a machine learning model. This value-based profiling also captures the values of the function pointers. Thus if a function pointer is passed as an argument to another function, then we are able to predict the function invocation based on the function pointer values.
We used LLVM to insert instrumentation calls for recording with acceptable performance. Higher depth is only required if there are too many rows with the same features but different mental that a max tree depth of 10 provided good accuracy. It embeds the decision tree within the application (i.e. inserts format. That final text file is read by an LLVM pass, which decision tree model is then written to file as a special text in the tables produced from the profiling phase. The learned the model and save it for later use. The python script reads sklearn.tree.DecisionTreeClassifier is used to learn sion tree API library to implement the machine learning model. The deci-

## 4.5 Implementation

We used LLVM to insert instrumentation calls for recording the call context for every library call within the application. The instrumented application was run using Pin JIT to generate the profile trace. The trace is then parsed to create a csv file with the training data. We use the Python scikit learn library to implement the machine learning model. The decision tree API

sklearn.tree.DecisionTreeClassifier is used to learn the model and save it for later use. The python script reads in the tables produced from the profiling phase. The learned decision tree model is then written to file as a special text format. That final text file is read by an LLVM pass, which embeds the decision tree within the application (i.e. inserts prediction calls for the runtime system). We found experimentally that a max tree depth of 10 provided good accuracy with acceptable performance. Higher depth is only required if there are too many rows with the same features but different outcomes, but adds the dilemma of overfitting the training data. We did not use boosting. Please refer to the appendix section 9.3 for additional details on decision tree learning.

## 5 Evaluation

We evaluate BlankIt using SPEC CPU 2006. SPEC has several properties that make it a good candidate for exercising and evaluating BlankIt. First, it is performance-oriented, so we can measure runtime overheads on realistic CPU-intensive benchmarks. Second, it has a standard library profile, which carries a relatively large CVE list. Lastly, call graphs of SPEC benchmarks and their supporting libraries are significantly dense and divergent, which are needed to stress the prediction framework. As an example, SPEC benchmarks invoke 63 glibc unique functions at runtime on an average; this leads to a 171-node, 378-edge static call graph with a max callchain depth of 7 (and in this case a function set of which only 5% are non-divergent) (see Table 3). A previous study [24] demonstrates input similarity based on basic block and branch execution frequencies, but the feature vector used for decision tree includes RDF and value separation (with the intuition that the call chain inside the library is a function of the values of its arguments). While the RDF can have a relationship with the similarity measure based on the branch frequency in [24], the values do not. Also, we predict the paths within the libraries, which are not analyzed by this work. Moreover, real-world applications have inputs that stress the program paths that can be used for training.

| SPEC benchmark and glibc graph metrics | Avg |
|----------------------------------------|-----|
| 1. # dynamically called glibc funcs from SPEC | 63  |
| 2. # statically reachable funcs in glibc based on (1) | 171 |
| 3. # callgraph edges based on static callgraph in (2) | 378 |
| 4. # non-divergent functions in (2) | 8   |
| 5. max static callchain depth of (2) | 7   |

Table 2: Key graph metrics for SPEC CPU 2006 and glibc

With the exception of the linker shared object and the vdso image, we have instrumented all the benchmarks’ shared objects. Table 3 shows the distribution of shared objects across the benchmarks. The most important is glibc-2.26 [23], a fundamental library for programs written in C and compiled on GNU/Linux systems. The library provides POSIX, BSD, OS-specific and other APIs. Some of the basic facilities include print, login, and crypt. Thus, glibc supports a wide range of applications, which is borne out in the table (100% dependence across all benchmarks). Historically, it has also been targeted and exploited heavily. The other libraries are libm 2.26, libgcc_s from the libgcc1 package v1:7.2.0-1ubuntu1 16.04, and libstdc++ 6.0.24 which are also tackled by BlankIt. Our runtime uses Pin v3.6. We have built SPEC with version 5 of LLVM, which fails to compile 400.perlbench. It generates multiple definitions for gnu_dev_major, minor, and other functions, so we have elided treatment of it here. All other C/C++ benchmarks are presented. The raw decision trees have a lot of compile time constant checks which after constant folding reduces the tree to few if else checks thus increasing.
binary size only modestly. All runtime overhead experiments
are on an Ubuntu 16.04.3 LTS machine with an AMD Ryzen
7 1800X 8-Core 3.6 GHz processor and 32 GB DD4 2666
MHz RAM. All the SPEC benchmarks were trained on “test”
(small) and “train” (medium) input data sets and were regres-
sion tested using the (large) “ref” input data sets. All runtime
experiments are averaged over three runs.

| Benchmark     | libc | libm | libgcc | libstdc++ |
|---------------|------|------|--------|------------|
| 401.bzip2     | ✓    | ✓    | ✓      | ✓          |
| 403.gcc       | ✓    | ✓    | ✓      | ✓          |
| 429.mcf       | ✓    | ✓    | ✓      | ✓          |
| 433.milc      | ✓    | ✓    | ✓      | ✓          |
| 444.namd      | ✓    | ✓    | ✓      | ✓          |
| 445.gobmk     | ✓    | ✓    | ✓      | ✓          |
| 450.soplex    | ✓    | ✓    | ✓      | ✓          |
| 453.povray    | ✓    | ✓    | ✓      | ✓          |
| 456.hmmer     | ✓    | ✓    | ✓      | ✓          |
| 458.sjeng     | ✓    | ✓    | ✓      | ✓          |
| 462.libquantum| ✓    | ✓    | ✓      | ✓          |
| 464.h264ref   | ✓    | ✓    | ✓      | ✓          |
| 470.lbm       | ✓    | ✓    | ✓      | ✓          |
| 471.omnetpp   | ✓    | ✓    | ✓      | ✓          |
| 473.astar     | ✓    | ✓    | ✓      | ✓          |
| 482.sphinx3   | ✓    | ✓    | ✓      | ✓          |
| 483.xalancbmk | ✓    | ✓    | ✓      | ✓          |

Table 3: Shared objects in SPEC CPU 2006 benchmarks

5.1 Security

What constitutes an attack surface, especially when preparing
for unknown future attacks, is difficult to capture. We present
three results for reducing dynamic linked functions. Taken
together, they offer three different axes for understanding
how BlankIt is behaving. They summarize (1) the number
of functions that are exposed, (2) the number of gadgets in a
known type of attack that are exposed, and (3) the number of
known functions from a vulnerable list that are exposed.

The first measure is a dynamic metric that describes the
maximum number of library functions exposed at any given
time during execution. This can be described by the following
formula:

\[ \text{exposed} = p + s + c \]  

(1)

where \( \text{exposed} \) is the maximum number of loaded functions
at runtime, \( p \) is the number of functions that Pin is unable to
instrument and thus must be left as they are (without blanking
them), \( s \) is the number of functions that are less than 14 bytes
and therefore too small for blanking, and \( c \) is the maximum-
length call chain for a given benchmark that our framework
dynamically loads at any call site during the execution. In
other words, the number of exposed functions in the worst
case is the maximum number of unblanked functions that
could be leveraged in some attack. The percent reduction of
code surface is then given by:

\[ \text{reduction} = \frac{\sum n_l - \text{exposed}}{\sum n_l} \times 100 \]  

(2)

where \( l \) is some library and \( n_l \) is the total number of functions
available at runtime in some library \( l \). This metric does not
capture anything about the inherent weaknesses or strengths
of the exposed functions - it only captures that they are ex-
posed. Table 4 presents this result in the first column as “% reduction in dynamic linked functions”. This worst-case re-
duction is, on average, 97.1%.

| Benchmark     | % Exposed Code Surface Reduction | % ROP Gadget Reduction | % glibc CVE Function Reduction |
|---------------|---------------------------------|------------------------|-------------------------------|
| 401.bzip2     | 97.7                            | 98.9                   | 95.7                          |
| 403.gcc       | 97.2                            | 97.8                   | 95.7                          |
| 429.mcf       | 94.5                            | 95.9                   | 95.7                          |
| 433.milc      | 98                               | 98.5                   | 95.7                          |
| 444.namd      | 97                               | 96.4                   | 93.6                          |
| 445.gobmk     | 95.7                            | 96.2                   | 93.6                          |
| 450.soplex    | 97.4                            | 99.3                   | 97.9                          |
| 453.povray    | 96.9                            | 97.7                   | 93.6                          |
| 456.hmmer     | 97.9                            | 97.9                   | 93.6                          |
| 458.sjeng     | 97.8                            | 98.9                   | 95.7                          |
| 462.libquantum| 97.9                            | 98.6                   | 95.7                          |
| 464.h264ref   | 97.9                            | 98.7                   | 95.7                          |
| 470.lbm       | 97.8                            | 98.6                   | 95.7                          |
| 471.omnetpp   | 95.6                            | 96.9                   | 95.7                          |
| 473.astar     | 96.6                            | 96.6                   | 95.7                          |
| 482.sphinx3   | 97.6                            | 98.2                   | 95.7                          |
| 483.xalancbmk | 96.9                            | 98.1                   | 91.5                          |

Table 4: Reductions metrics (DLF = Dynamic Linked Function)

The results show a very high percentage reduction; signifi-
cantly more than any static or dynamic technique can achieve.

Return-oriented programming depends on ROP gadgets in
the code in order to carry out an effective attack. To measure
the reduction in gadgets, we leveraged ROPgadget [47], an
analysis tool for enumerating the ROP gadgets in a binary.
Because BlankIt is a dynamic technique, the number of gad-
ggets varies over time. Thus, similar to before, we choose the
worst-case scenario at any given point in the program and
report its ROP gadget reduction. As before, we calculate the
maximum number of exposed gadgets (similar to equation 1),
and then calculate the reduction by summing over the number
of gadgets in the text section in each library, subtracting out
the exposed gadgets, and gathering the percentage (as in equa-
tion 2). Table 4 shows the benefits of BlankIt on ROP gadget
reduction. The average is 97.8%. Please refer to the appendix
section 9.1 for details on the quality of these gadgets.
The last metric is a measure of the functions in glibc CVEs that are removed by BlankIt. We reviewed the list of all 95 CVEs for glibc, which reach back to year 2000, and we identified all unique functions mentioned in the descriptions. Of these, we identified 47 that are unequivocally loaded by glibc in the SPEC suite. That is, there must be an exact match in the dynamically loaded list of glibc functions for a function related in a glibc CVE to be considered. For example, “alloca” is mentioned in CVE-2015-1473, but it is not explicitly exported with that name and so is discarded, even though there are multiple allocation functions. Then the number of exposed CVE functions is obtained as follows:

\[ \text{exposed CVE} = p + s + a \]  

where \( p \) and \( s \) are uninstrumented due to Pin or too small to instrument (as before), but \( a \) represents any function that is called that is in the CVE function list. The percentage is then taken out of the 47 CVE functions. This metric should not be misunderstood as the number of CVEs since 2000 that are thwarted by BlankIt. Rather, it classifies functions as vulnerable based on their CVE history, and then asks how many such functions are exposed under BlankIt running a common benchmark. The results are shown in the last column of Table 4. The average reduction is 95.1%.

5.2 Runtime

Figure 5 shows the runtime overhead. There are three bars per benchmark: native, BlankIt for glibc, and BlankIt for all libs. The most crucial library for security purposes is glibc (the middle bars for each benchmark in the graph). The average slowdown for a BlankIt-enabled application on only glibc is 16%. There is a slight speedup in the case of lbm, which can be accounted for by variance. The rest perform reasonably well, with gcc being the worst at 1.76x. The slowdown for gcc (and similarly, for sjeng) is due to heavy usage of libc. Runtime overhead is primarily due to library call frequency and not due to misprediction. Thus, while prediction accuracy was poorest for libquantum (discussed in the next section), the performance was good. In this BlankIt prototype the audit thread runs in parallel and “keeps up” with the mispredict frequency and does not add extra blocking. There are still open optimization opportunities to improve the performance, which may include compiler-based hoisting operations to pull prediction probes outside of loops.

The rightmost bars represent a BlankIt-enabled application on all libraries. In some cases, (bzip2, gcc, mcf, sjeng) the results are almost identical to a glibc-only result because they link against no other libraries. In other cases, adding the libraries costs little in overhead for the extra security. The average slowdown for BlankIt over all libs is 18%, demonstrating that BlankIt likely scales well across programs’ dynamic library sets.

5.3 Prediction

Our treatment of prediction includes our observations while working with the framework, accuracy results and analysis on SPEC, and then a breakdown of the kinds of mispredictions that were measured.

5.3.1 Observations

In the case of library functions, especially in languages like C that do not have a context for library function calls, we have observed that the set of functions called within the library can be predicted based on the dynamic calling context. The necessary dynamic calling context is discovered by the decision tree which can as simple as just the name of the function and/or the call site.

However, some times the call chain is dependent on the arguments passed to the function, which could include a function pointer. For example, there might be a math library function that calls a different set of internal functions based on the arguments. The decision tree is able to handle such cases by training on the values passed to the function. It is able to model the different call chains that are invoked based on the range of values of the function parameters encountered during profiling. This value-based approach handles function pointers as any other value. That is, if a function takes a function pointer as an argument, then based on the value of the pointer, different call chains will be invoked. If the profiling data has all possible values that a function pointer can take, then our decision tree is able to train on them to predict the right call chain, depending on the function pointer value.

The decision tree is currently unable to capture other use cases like the presence of multiple threads or certain special system states or error conditions which were not triggered during profiling.

5.3.2 Accuracy and Audit overhead

Table 5 shows the prediction accuracy and audit overhead for the SPEC2006 benchmark suite. Over half of the accuracies are 97% or greater; three are 100%; and the average is 94.3%. As a matter of fact, the decision tree’s prediction ability was tested for predicting every function in SPEC2006 at every call site and was found to be very close to the one reported here for the libraries.

One of the important reasons for very high prediction accuracy stems from the fact that libraries follow software design patterns; the use cases of libraries are therefore finite and can be siloed. Our decision trees are able to learn these patterns which are input-related and during regression testing are able to pinpoint the silo and its underlying set of function calls. The only application for which the decision tree accuracy was relatively low is libquantum. For this application, there was a call chain involving cfree and cfree followed by munmap in train and ref inputs, respectively, which is one of the major
Figure 6: Runtime slowdown for BlankIt on SPEC 2006 CPU, normalized against native.

| Benchmark       | % Accuracy | Audit (µs) |
|-----------------|------------|------------|
| 401.bzip2       | 91         | 287        |
| 403.gcc         | 99         | 12         |
| 429.mcf         | 94         | 92         |
| 433.milc        | 100        | 27         |
| 444.namd        | 99         | 11         |
| 445.gobmk       | 84         | 8          |
| 450.soplex      | 92         | 26         |
| 453.povray      | 97         | 6          |
| 456.hmmer       | 98         | 6          |
| 458.sjeng       | 97         | 27         |
| 462.libquantum  | 60         | 41         |
| 464.h264ref     | 100        | 28         |
| 470.lbm         | 98         | 171        |
| 471.omnetpp     | 99         | 6          |
| 473.astar       | 100        | 58         |
| 482.sphinx3     | 99         | 11         |
| 483.xalancbmk   | 96.9       | 18         |

Table 5: Call Chain Prediction Accuracy and Audit Overhead

The audit overhead is reported as the geometric mean of mispredicted function runtime within valgrind. The results add confidence that running an audit in parallel is tenable.

The audit overhead is reported as the geometric mean of mispredicted function runtime within valgrind. The results add confidence that running an audit in parallel is tenable. The total library function call counts are not reported, but as a typical example, lbm has 2,626,463 runtime library calls (and 98% prediction accuracy). lbm takes roughly 250s to execute under BlankIt. Thus, a 171µs overhead per mispredict falls well within the 210 mispredictions that occur per second. This shows that doing full program stops until Valgrind reports back is plausible.

5.3.3 Misprediction Breakdown

We further classify the mispredictions into overpredictions (where more functions were loaded than necessary) and underprediction (where lesser number of functions loaded than necessary). In almost all the cases, there were under-predictions (100%) except in case of gcc (where the under and over predictions were almost equal) and soplex (where there were under-predictions 93%). The main reason is that when the decision tree encounters a call-site which was not exercised during training, it is extremely conservative and bases the prediction on whether the entry function was seen during training; due to these reasons it chooses a subset of functions that were callees of the entry functions. This in turn provides good security since no spurious functions are brought in that could increase the exposed code surface.

5.4 Multithreading and Windows

BlankIt is not limited to single-threaded programs, neither in its general approach nor current implementation, nor is it OS-specific. BlankIt can leverage Intel Pin’s threading support and add a synchronized blanking/un-blanking mechanism for parallel programs. The thread that blanks (or fills) a piece of code would have to acquire a lock for that particular code section to do so (page granularity in Linux). Similarly, BlankIt can also be ported to Windows without any design or conceptual changes: mprotect can be replaced by VirtualProtect, msvcrtd.dll protected in place of glibc, etc.

6 Case Study

We study how a recent vulnerability in glibc, CVE-2018-11236 [14] on buffer overflow is handled by BlankIt. CVE-2018-11236 is a vulnerability that exists in glibc version 2.27
and earlier in the realpath function in stdlib/canonicalize.c. The function realpath intakes a pathname as one of its arguments. If a pathname that has length close to SSIZE_MAX is passed as an argument, it causes a buffer overflow that overwrites the stack on line 191 in Code 3. This overflow can be exploited to jump to any ROP/JOP gadget and carry out a Turing-complete attack. With BlankIt, however, jumping to any arbitrary location is not possible, as the code sections are blanked. CFI mechanisms would limit arbitrary jumps, as well. However, in CFI the attacker can jump to a legit function with exploitive inputs and carry out the attack. BlankIt catches the attack if the call to this function is not predicted in the path. Further, if the function realpath is never used, then BlankIt never loads it, catching any attempt to attack through the function.

```
183 extra_buf = _-_alloca (path_max);
184 len = strlen (end);
185 if (path_max - n <= len)
186 {
187     __set_errno (ENAMETOOLONG);
188     goto error;
189 }
190 /* Careful here, end may be a pointer into extra_buf... */
191 memmove (&extra_buf[n], end, len + 1);
```

Code 3: CVE-2018-11236

7 Related Work

The two main lines of research that are closely related to security-focused debloating are software debloating and security vulnerability techniques.

The embedded software community performed debloating based on link-time optimizations in order to reduce code size. As mentioned earlier, compiler based link-time optimizations involve statically determining a set of functions to be removed from the linked library. The key goal of such link time optimizations is to compact the code size [4, 16]. While such solutions [21, 37] have shown to substantially reduce the code size, they are not geared towards solving the security issues due to bloated libraries. This is because static link time optimizations err on the conservative side. A load time mechanism such as piece-wise compilation [46] reduces approximation but relies on a CFI mechanism for defense against the ROP gadget exploitation in the loaded functions. A new direction of code debloating based on programmer specifications was developed in [25]. These problems are different from the goal of BlankIt, which reduces the number of dynamic functions linked so that the possibilities of constructing malicious programs diminishes significantly.

Debloating is an active research topic within the software engineering community and oftentimes with respect to performance. Mitchell et al. [34] investigated causes of bloat and how “health signatures” can describe memory footprints in a way that lends itself to value judgments about the strength of a software design. In a similar work, a tool called Yeti was developed to help identify costly data structures [32]. Regarding performance, Xu et al. [60] argue that memory bloat is a more severe problem given reduced scaling of chip real estate due to Moore’s law. Other research is on understanding excessive abstractions or object creation in Java and how these affect performance [53]; on identifying heavy computations that have little benefit (e.g. constructing a large object only to check its size) [59]; on debloating container objects due to their negative impact on performance [57]; and on reusing data structures rather than recreating them to boost performance [58]. While this work has paved some of the way for debloating, it is not geared towards security and thus can not be directly applied to the problem of reducing exposed code surface.

The lack of memory safety in languages such as C/C++ has been a pernicious and long-lasting problem, and a vast number of potential solutions have been proposed. Real world exploits show that all currently deployed protections can be defeated, and in fact new vulnerabilities are reported frequently [13, 21, 50]. Memory safety mechanisms can safeguard against many of the memory corruption attacks, however, is ≥2X slower in case of source based memory safety techniques like CETS [38] and ≥10X slower in case of binary based ones like Dr.Memory [8]. There has been work on control pointer integrity (CFI) checking [5, 28], Address Space Layout Randomization [49], as well as control flow integrity (CFI) checking [10, 22, 30, 63]. In spite of such advancements, in [18] authors show an attack called Control Jujutsu that exploits the imprecision of scalable pointer analysis to bypass fine-grained enforcement of CFI. Control-Flow Bending [10] (CFB) showed that even a fully-precise static CFI cannot defend against many non-control data attacks. In addition to these attacks, there are many DoS (denial of service) and privilege escalation attacks documented in [13] that are unrelated to the issue of control flow and could have severe implications for the security of the linked application. As discussed earlier in the introduction, BlankIT prevents some attacks that escape detection techniques based on CFI and CPI.

8 Conclusion

In this work, we propose and show how to effectively implement a scheme of demand-driven loading to reduce the exposed code surface of vulnerable linked libraries. We achieve this by capturing control dependence of library call sites (via reverse dominance frontiers) and by training decision trees to establish input-relatedness. We also devise a highly effective, very low overhead, binary-level mechanism. It dynamically loads the needed functions at a given call site and blanks out the unneeded ones, which significantly weakens an attacker’s ability to construct gadgets. Our results on the full SPEC2006 benchmark suite (evaluated with its 4 major user-
level libraries, libc, libm, libgcc and libstdc++) are very strong: the prediction accuracy in most cases being at least 97%, and dynamic linked functions and ROP gadget reduction likewise being at least 97%. On average, the runtime overhead with BlankIt is 18%, across full set of SPEC benchmarks which is within tolerable limits. BlankIt also catches few cases of non-control data attacks and some which are not tackled by CFI and CPI in general. BlankIt has all these benefits without recompiling any linked binaries.

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9 Appendix

9.1 Quality of Gadgets

| Benchmark     | Gadget quality | BlankIt Gadget quality |
|---------------|---------------|------------------------|
| 401.bzip2     | 0.81          | 1.25                   |
| 403.gcc       | 0.81          | 1.07                   |
| 429.mcf       | 0.81          | 1.14                   |
| 433.milc      | 0.75          | 1.29                   |
| 444.namd      | 0.77          | 0.97                   |
| 445.gobmk     | 0.75          | 0.84                   |
| 450.soplex    | 0.77          | 0.96                   |
| 453.povray    | 0.77          | 1.12                   |
| 456.hmmer     | 0.75          | 1.19                   |
| 458.sjeng     | 0.81          | 1.15                   |
| 462.libquantum| 0.73          | 0.79                   |
| 464.h264ref   | 0.75          | 1.15                   |
| 470.lbm       | 0.75          | 1.35                   |
| 471.omnetpp   | 0.77          | 1.08                   |
| 473.astar     | 0.77          | 1.15                   |
| 482.sphinx3   | 0.75          | 0.97                   |
| 483.xalancbmk | 0.77          | 0.98                   |

Table 6: ROP Gadget Quality in SPEC CPU 2006 with and without BlankIt (higher indicates better security)

We would like to present details on the quality of gadgets with respect to BlankIt. Gality [20] is a tool that measures the quality of the gadgets for the ease of constructing an attack and provides an overall score. In details, the tool first categorizes the gadgets, finding the distribution of different gadgets available in the arsenal of the attacker. The tool also checks the side effects of a gadget. A side-effect is measured by the number of preconditions that must be satisfied for using a gadget. In other words, a high quality gadget is one with no pre-conditions or that does not affect any other register or memory by overwriting the value and thus giving away the attack. The Gality score starts at 0 and is increased for side-effects and pre-conditions. Thus higher score indicates worse gadget quality hence better security. As shown in Table 6 BlankIt consistently has higher scores thus signifying that BlankIt offers better security.

9.2 Non-Control Data Attack Defense

We demonstrate non-control data attack that is mitigated by BlankIt. In Figure 4 the arguments of the library function are copied at the latest available point, which is at either the PHI function or the definition (whichever is the reaching definition). The copies are passed to the auditor process during...
misprediction. Any input-based overflow within the library is caught by Valgrind. However, if the input to the library is modified within the application and results in a valid program flow, then Valgrind does not report an error. Thus, in cases where the input to the library is modified after the latest availability point of an argument, BlankIt can catch the attack by comparing the predicted call chain with the call graph reported by the auditor process. In the example, input 'a' is modified through buffer overflow in ‘strcpy(b,input)’ and results in a misprediction. However, the predicted chain matches with the call graph reported by the auditor, thus catching the attack and raising an alarm. During actual misprediction, the Valgrind call chain matches the observed call chain and not the predicted call chain and thus, declares it as legal execution.

9.3 Decision Tree Learning

The decision tree is a machine learning model based on inductive inference and which satisfies BlankIt’s requirement for quick runtime lookup. It is trained on a set of input attributes and the observed output by correlating the observed output with a disjunction of conjunctions of predicates on the input attributes [35]. The decision tree tests a predicate on one of the input attributes at every node. Depending on the outcome of the predicate, one of the outgoing edges is followed to the next node and halts when a leaf node is reached. A leaf node represents a class label, which is the prediction for the given input. In our model, the input is the context leading up to a call site, and the output is the call graph of the callee function. The context at a call site is the call site itself, the function that is called, and the function argument values. Given the context at a call site for a callee function $F$, the model will predict the set of functions within the library called through $F$. 