TANA: Precise Fine-grained Side-channel Information Leakage Quantification in Binaries

Anonymous

***Abstract*—Side-channel attacks allow attackers to infer some sensitive information based on non-functional characteristics. Existing works on address-based side-channel detection can provide a list of potential side-channel leakage sites. However, they 1) only consider the "average" information leakage which often neglect severe attack scenarios, 2) cannot accurately report the sum of multiple information leakages from various sites at one time.**

To overcome the above limitations, we propose a novel method to quantify the information leakage more precisely. The key insight is XXXXX. We have developed a tool called TANA, which can not only find the side-channel vulnerabilities but also estimate how many bits are actually leaked. TANA works in three steps. First, the application is executed to record the trace. Second, TANA runs the instruction level symbolic execution on the top of the execution trace. TANA will find side-channel information leakages and model each leakage as one unique math constraint. Finally, TANA will classify those constraints into independent multiple groups and run the Markov Chain Monte Carlo to estimate the information leakage. TANA can report a very fined-grained vulnerability result compared to the existing tools.

We applied the tool on OpenSSL, MbedTLS and libjpeg and found several serious side-channel vulnerabilities. Compared with previous research, the results are surprisingly different that most of the reported vulnerabilities are hard to exploit in practice.

I. Introduction

Side channels are hardly avoided in modern computer systems as the sensitive information may be leaked by kinds of neglected behaviors, such as power, electromagnetic radiation and even sound []. Among them, software-based side-channel vulnerabilities are especially common and have been studied for years []. The vulnerability results from vulnerable software codes and shared hardware components. As the threat model in Figure **??**, there is an information flow with secrets. By observing the outputs or hardware behaviors, attackers could infer the program execution and guess the secrets such as encryption keys [].

Various countermeasures have been proposed to defend against software-based side-channel attacks by reducing the shared resources and eliminating the leak paths [1]–[3]. In addition to runtime overheads, they are limited to specific hardwares. So it is imperative to discover and fix side channel vulnerabilities in advance and automatic detection methods are proposed recently [].

In general, both static analysis and dynamic analysis can be used to detect software-based side-channel vulnerabilities. Statically, XXXXXX. And dynamically, XXXXX. These works help to find a list of hidden vulnerabilities in real-world softwares, but fail to report how severe a potential leakage site could be. Many of the reported vulnerabilities are typically hard to be exploited and leak very little information (e.g., one bit of the length of the key [2]). For example, the vulnerabilities in OpenSSL library are assigned with low severity and not considered in the threat model now [**?**]. It is worthwhile to have a tool to tell how much information is actually leaked and help to fix them.

To assess side-channel vulnerabilities, the first problem is that we need a proper quantification metric . Although tools based on static analysis with abstract interpretation can give an upper bound, which is useful to justify whether the implementation is secure enough, they can't indicate the leakage is seuvere or not due to the over-approximation []. The dynamic methods will take a concrete input and run the program actually, which should be very precise in term of real leakage, but they suffer from the incompleteness of testing and trade-off of performance and accuracy [].

Secondly, open source libraries may have multiple leakage sites, which can be exploited for attackers at one time [4]–[6]. It is necessary to know how much information is actually leaked in total. No existing tools can practically estimate the total information leakage from multiple leakage sites in real-world libraries. Simply adding the results together gets a very rough upper bound of the total information leakage if those leakages aren't independent.

To overcome the above limitations, we propose a novel method to more precisely quantify the information leakage. Previous work only considers the "average" information leakage which often neglects severe scenarios. The average information assumes that the target program will have **different** sensitive information as the input when the attacker launches the attack, which often does not match the attack scenario. During the real side-channel attacks, an adversary may run the target problem again and over again with the fixed unknown sensitive information as the input. Therefore, the previous threat model can't catch real attack scenarios.

In contrast, our method is more precise and fine-grained. For our analysis, the input key is fixed. We classify the address-based side-channel vulnerabilities into two categories: 1.*secret-dependent control-flow transfers* and 2.*secret-dependent data access* and model them with the math formulas which constrain the value of sensitive information. We define the amount of leaked information as the number of possible solutions that can reduced after applying each constrains. It is interesting to mention that the definition is different from the definition in previous static-based analysis tools. Before the attack, the adversary has a big but finite input space. Every time the adversary observes one leakage site, he can

eliminate some potential input and reduce the size of the input space. The smaller the input space is, the more information is actually gained. On an extreme situation, if the size of the input space reduces to one, the adversary can determine the input information uniquely, which means the total information is leaked. We define the leaked information as the proportion of the number of possible input that satisfies the attacker's observation.

Our method can identify and quantify address-based sensitive information leakage sites in real-world applications automatically. Adversaries can exploit different control-flow transfers and data-access patterns when the program processes different sensitive data. We refer them as the potential information leakage sites. Our tool can discover and estimate those potential information leakage sites as well as how many bits they can leak. We are also able to report precisely how many bits can be leaked in total if an attacker observes more than one site. We run symbolic execution on execution traces. We model each side-channel leakage as a math formula. The sensitive input is divided into several independent bytes and each byte is regarded as a unique symbol. Those formulas can precisely model every the side-channel vulnerability. In other words, if the application has a different sensitive input but still satisfies the formula, the code can still leak the same information. Those information leakage sites may spread in the whole program and their leakages may not be dependent. Simply adding them up can only get a coarse upper bound estimate. In order to accurately calculate the total information leakage, we must know the dependent relationships among those multiple leakages sites. Therefore, we introduce a monte carlo sampling method to estimate the total information leakage.

We implement the proposed method as a tool named TANA which can precisely discover and quantify the leaked information. We apply TANA on several crypto and non-crypto libraries including OpenSSL, MbedTLS and libjpeg. The experiment result confirms that TANA can precisely identify the pre-known vulnerabilities, reports how much information is leaked and which byte in the original sensitive buffer is leaked. The result shows that while those crypto libraries have a number of side-channels, most of them actually leak very little information. Also, we also use the tool to analysis the two reported side-channel attack in the libjpeg library. Finally, we present new vulnerabilities. With the help of TANA, we confirm those vulnerabilities are easily to be exploited. Our results are superisingly different compared to previous results and much more useful in practice.

In summary, we make the following contributions:

- We propose a novel method that can quantify fine-grained side-channel information leakages. We model each information leakage vulnerability as math formulas and mutiple side-channel vulnerabilities can be seen as the disjunctions of those formulas, which precisely models the program semantics.
- We transfer the information quantification problem into a probabilty distribution problem and use the Monte Carlo sampling method to estimate the information leakage. Some initial results indicate the the sampling method suffers from the curse of dimensionality problem. We therefore design a guided sampling method and provide the corresponding error esitimate.
- We implement the proposed method into a practical tool and apply it on several real-world software. TANA successfully identify the address-based side-channel vulnerabilities and provide the corresponding information leakge. The information lekage result provide the detailed information that help developers to fix the vulnerability.

II. Background

In this section, we first present a basic introduction to the memory-based side-channel attacks. Those attacks are what we attempt to study in the paper. After that, we will show existing methods on side-channel detections and quantifications.

A. Address-based Side-Channels

Address-based side-channels are information channels that can leak sensitive information unintendedly through different behaviors when the program accesses different memory addresses. Fundamentally, those differences were caused by the memory hierarchy design in modern computer systems. When the CPU fetches the data, it first searches the cache, which stores copies of the data that was frequently used in main memory. If the data doesn't exist in the cache, the CPU will read the data from the main memory (RAM). According to the layer that causes the side-channels, we classify the address-based side channels into two categories: cache-based side-channel attacks and memory-based side-channel attacks.

1) Cache-based Attacks: In general, the cached-based side-channels seek information relying on the time differences between the cache miss and the cache hit. Here we introduce two frequently used cache attacks: PRIME+PROBE, FLUSH+RELOAD.

PRIME+PROBE targets a single cache set. It has two phases. During the "prime" phase, the attacker fills the cache set with his data. In the second "probe" phase, the attacker reaccesses the cache set again. If the victim accesses the cache set and evicts part of the data, the attacker will experience a slow measurement. If not, the measurement will be fast. By knowing which cache set the target program that accesses, the attacker can infer part of the sensitive information.

FLUSH+RELOAD targets a single cache line. It requires the attacker and victim share the same memory. It also has two phases. During the "flush" stage, the attacker flushes the "monitered memory" from the cache. Then the attacker waits for the victim to access the memory. In the next phase, the attacker reload the "monitored memory". If the time is short, which indicates there is a cache hit and the victim reloads the memory before. On the other hand, the time will be longer since the CPU need to reload the memory into the cache line.

2) Memory-based Attack: Memory-based side-channel attack [5] exploits the different behaviors when the program accesses different page tables. For example, the controlled-channel attack [5], which works in the kernel space, can infer

the sensitive data in the shielding systems by observing the page fault sequences after restricting some code and data pages.

After examing the memory-based side-channels attack. We believe the root cause of those attacks are secret-dependent memory access and control flow transfers.

```
1  void sample_encrypt_setup
2                 (encrypt_ctx *ctx,
3                 const unsigned char *key)
4  {
5      int i, j, k;
6      unsigned char *m, T[256];
7      m = ctx->m;
8      for(i = 0 ; i < 256; i++, k++)
9      {
10         // Secret Dependent Memory Access
11         m[i] = Table[key[k] % 256];
12         // Secret Dependent Control Flow Transfer
13         if(key[k] == 0)
14         {
15             m[i] = k * key[i];
16             m[i] = m[i] % 256;
17         }
18     }
19 }
```

Listing 1: Sample code shows secret-dependent memory access and secret-dependent control-flow transfer.

For example, the above code 1 show a simple encryption function that has the two kinds of side-channels. At line 11, depending on the value of a key, the code will access the different entry in the predefined table. At the line 13, the code will do a series of computation and determine if the code in the if branch is executed or not. Such vulnerabilities are called the memory-based side-channles. We identify and quantify the leakage of the two kinds of vulnerabilities in the paper.

B. Information Leakage Quantification

Given an event e which occurs with the probability $P(e)$, if the event e happens, then we receive

$$I = -\log_2 P(e)$$

bits of information by knowing the event e.

The above definition is obvious. Suppose a char variable a in C program has the size of one byte (8 bits), so the value in the variable can range from 0 - 255. We assume the *a* has the uniform distribution. If at one time we observe the a equals to 1, the probability will be $\frac{1}{256}$. So the information we get is $-\log(\frac{1}{256}) = 8$ bits, which is exactly the size of the char variable in the C program.

Existing works on information leakage quantification are based on mutual information or min-entropy [7]. In their frameworks, the input sensitive information K is viewed as a random variable. Let k_i be one of the possible value of K. The Shannon entropy $H(K)$ is defined by

$$H(K) = -\sum_{k_i \in K} P(k_i) \log_2 P(k_i)$$

The Shannon entropy can be used to quantify the initial uncertainty about the sensitive information. Suppose a program (P) with the K as the sensitive input, an adversary has some observations (O) through the side-channels. In this work, the observations are referred as the secret-dependent control-flows and secret-dependent data-access patterns. The conditional entropy $H(K|O)$ is

$$H(K|O) = -\sum_{o_j \in O} P(o_j) \sum_{k_i \in K} P(k_i|o_j) \log_2 P(k_i|o_j)$$

Intuitively, the conditional information marks the uncertainty about K after the adversary has gained some observations (O).

Many previous works use the mutual information $I(K;O)$ to quantify the leakage which is defined as follows:

$$\mathit{Leakage} = I(K;O) = \sum_{k_i \in K} \sum_{o_j \in O} P(k_i, o_j) \log_2 \frac{P(k_i, o_j)}{P(k_i)P(o_j)}$$

where $P(k_i, o_i)$ is the joint discrete distribution of K and O. Alternatively, the mutual information can also be computed with the following equation:

$$\mathit{Leakage} = I(K;O) = H(K) - H(K|O) = H(O) - H(O|K)$$

For a deterministic program, once the input K is fixed, the program will have the same control-flow transfers and data-access patterns. As a result, $P(k_i, o_j)$ will always equals to 1 or 0. So the conditional entropy $H(O|K)$ will equal to zero. So the leakage defined by the mutual information can be simplified into:

$$\mathit{Leakage} = I(K;O) = H(O)$$

In other words, once we know the distribution of those memory-access patterns. We can calculate how much information is actually leaked.

Another common method is based on the maximal leakage [1], [7], [8]. The formal information theory can prove that the maximal leakage is the upper bound of the mutual information (Channel Capacity).

$$\mathit{Leakage} = \log(C(O))$$

$C(O)$ represents the number of different observations that an attacker can have.

Now we provide a concrete example to show how the two types of quantification definition works.

Maximal leakage Depending on the value of key, the code can run four different branches which corrosponding to four different observations. Therefore, by the maximal leakage definition, the leakage equals to $\log 4 = 2$ bits.

```
unsigned char key = input();
// key = [0 ... 255]
if(key = 128)
    A(); // branch 1
else if (key < 64)
    B(); // branch 2
else if (key < 128)
    C(); // branch 3
else
    D(); // branch 4
```

Listing 2: A simple program

Branch	A	B	C	D
Possibility	1/256	64/256	64/256	127/256

TABLE I: The distribution of observations

Mutual Information If the key satisfies the uniform distribution, the probability of the code runs each branch can be computed with the following result: Therefore, the leakage equals to $\frac{1}{256}\log\frac{1}{256} + \frac{1}{4}\log\frac{1}{4} * 2 + \frac{127}{256}\log\frac{127}{256} = 1.7$ bits.

III. Threat Model

We consider an attacker who shares the same hardware resource with the victim. The attacker attempts to retrieve sensitive information via memory-based side-channel attacks. The attacker has no direct access to the memory or cache, but can probe the memory or cache at each program point. In reality, the attacker will face many possible obstacles, including the noisy observations, limited observations on memory or cache. But for this project, we assume the attacker can have noise-free observations. The threat model captures most of the cache-based and memory-based side channel attacks. We only consider the deterministic program for the project.

IV. Overview

The shortcomings of the existing work inspire us to design a new tool to detect and quantify information leakage vulnerabilities in binaries. The tool has three steps. First, we run the target program with the concrete input (sensitive information) under the dynamic binary instrumentation (DBI) frameworks to collect the execution traces. After that, we run the symbolic execution to capture the fined-grained semantic information of each secret-dependent control-flow transfers and data-accesses. Finally we run the Markov Chain Monte Carlo (MCMC) to estimate the information leakage.

1) *Execution trace generation.* The design goal of TANA is to estimate the information leakage as precisely as possible. Therefore, we sacrifice the soundness for the precision in terms of program analysis. Previous works [2], [3] have demonstrated the effectiveness of the dynamic program analysis. We run the target binary under the dynamic binary instrumentation (DBI) to record the execution trace and the runtime information.
2) *Instruction level symbolic execution.* We model the attacker's observation about the side-channel vulnerabilities with math formula. Each formula capture the fined-grained information between the input secrets and the leakage site. For the consideration of precision and performance, we remove the intermediate language(IR) layer of the symbolic execution. Also, the engine only symbolically execute the instruction that might be affected the input key. The above design significantly reduces the overhead of the symbolic execution, which make the tool scales to real-world programs.
3) *Leakage estimation.* We transfer the information leakage quantification problem into the problem of counting the number of assignments that satisfy the formulas which models the observations from attacker. We propose a markov monte carlo method to estimate the number of satisfied solutions. With the help of Chebyshev's Inequality, we also give the an error estimate with the probability.

V. Chanllenges

In this section, we articulate several chanllenges and existing problems in quantifying the side-channel vulnerability leakages. We describe the chanllenges and then briefly present the corresponding solution.

A. Information Leakage Definition

Existing static-based side-channel quantification works [1] define information leakage as the mutual information or the maximal leakage. These definitions provide a strong security guarantee when trying to prove a program is secure enough if the their methods calculate the program leaks zero bits of information.

However, the above definition is less useful to justify the sensitive level of leakage sites. Considering the example code 2 in the previous section, if an attacker knows the code executes branch A by some observations, the attacker can know the key actually equals to 128. Suppose it is a dummy password checker, in which case the attacker can fully retrieve the password. Therefore, the total information leakage should be 8 bits, which equals to the size of unsigned char. According to the mutual definition, however, the leakage will be 1.7 bits. The maximal information leakage is 2 bits. Both approaches fail to tell how much information is actually leaked during the execution precisely.

The problem with the existing methods is that they are static-based and the input values are neglected by the previous definition. They assume the attacker runs the program multiple times with many different sensitive information as the input. Both the mutual information and the max-leakage give an "average" estimate of the information leakage. But it isn't the typical scenario for an adversary to launch the side-channel attack. When a side-channel attack happens, the adversary wants to retrieve the sensitive information, in which case the sensitive information is fixed (e.g. AES keys). The adversary will run the attack over and over again and guess the value bit by bit. Like the previous example, the existing static method doesn't work well in those situations.

Solution: In the project, we hope to give a very precise definition of information leakages. Suppose an attacker run the target program mutiple times with one fixed input, we want to know how much information he can infer by oberserving the memory access patterns. We come to the simple slogan [7] where the information leakage equals:

initial uncertainty - remaining uncertainty

If an adversary has zero knowledge about the input before the attack. The initial uncertainty equals to the size the input. As for the remaining uncertainty, we come to the original definition of the information content.

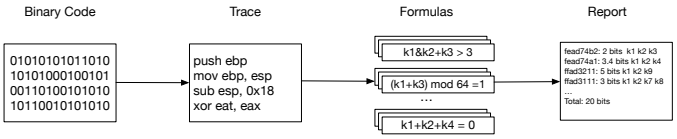
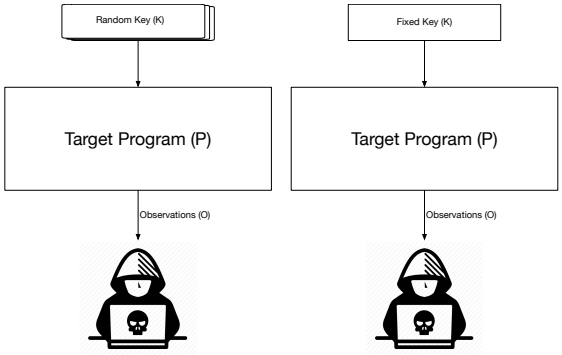


Fig. 1: The workflow of TANA



(a) Mutual Information (b) Real Attack

We quantify the information leakage with the following definition.

Definition 1. *Given a program P with the input set K, an adversary has the observation o when the input $k \in K$. We denote it as*

$$P(k) = o$$

The leakage L_{Pko} based on the oberservation is

$$L_{Pko} = log_2|K| - log_2|K^o|$$

where

$$K^o = \{k^{'} | k^{'} \in K \ and \ P(k^{'}) = o\}$$

With the new definition, if the attacker observes that the code 2 runs the branch 1, then the $K^{o^1} = \{128\}$. Therefore, the information leakage $L_{Pko^1} = log_2 256 - log_2 1 = 8$ bits, which means the key is totally leaked. If the attacker observes the code runs other branches, the leaked information is shown in the following table.

Branch	1	2	3	4
K^o	1	64	64	127
L_{Pko}(bits)	8	2	2	1

TABLE II: The leaked information by the definition 1

With the same definition 1, if the attacker observes that the code run branch 2, the information leakage will be 2 bits. The conclusion is consistent with the intuition. Because if the branch 2 was executed, we can know the key is less than 64. So we know the most and the second significant digits of the value key equals to 128.

B. Multiple Leak Sites

Real-world software can have various side-channel vulnerabilities. Those vulnerabilities may spread in the whole program. An adversary may exploit more than one side-channel vulnerabilities to gain more information [4], [5]. In order to precisely quantify the total information leakage, we need to know the relation of those leakage sites.

```
1  unsigned char k1, k2, k3;
2  ...
3  t1 = T[k1 % 8];         // Leakage 1
4  t2 = T[k2 % 8];         // Leakage 2
5  t3 = T[k3 % 8];         // Leakage 3
6  bool flag = foo(t1, t2, t3);
7  if(flag) {
8      if(k1 > 128)        // Leakage 4
9          A();
10 }
11 else {
12     if(k2 > 128)        // Leakage 5
13         B();
14 }
15 if(k1 + k2 + k3 > 128) // Leakage 6
16     C();
```

Listing 3: Multiple leakages

Considering the running example in 3, in which $k1$, $k2$ and $k3$ are the sensitive key. The code has six different leakage. Leakage 1, 2, 3 are the secret-dependent data accesses and leakage 4, 5, 6 are the secret-dependent control-flow transfers. The attacker can infer the last three digits of $k1$, $k2$, $k3$ from leakage 1, 2, 3. So those leakages are independent. For leakage 1, 4, 6, however, we have no idea about the total information leakage.

Suppose one program has two side-channel vulnerabilities A and B, which can leak L_A and L_B bits according to the definition 1. The total leaked information is noted as L_{Total}. The relation between A and B have the following three cases.

1) Independent Leakages: If A and B are independent leakages, the total information leakage will be:

$$L_{total} = L_A + L_B$$

2) Dependent Leakages: If A and B are dependent leakages, the total information leakage will be:

$$\max\{L_A, L_B\} <= L_{total} < L_A + L_B$$

3) Mutual Exclusive Leakages: If A and B are mutual exclusive leakges, then only A or B can be observed for one fixed input. The total information leakage will be L_A or L_B.

According to above definition, leakage 1, 2, 3 are independent leakages. Leakage 4, 5 are mutual exclusive leakages. For real-world applications, it is tough to estimate the total

leaked information for the following reasons. First, the real-world applications have more than thousands of lines of code. Side-channel vulnerabilities exist in many different locations of the source code. One leakage site leaks the temporary value. But the value contains some information about the original buffer. It is hard to know how the the sensitive value affects the temporary value. Second, some leakages sites may be dependent. The occurrence of the first affects the occurrence of the second sites. We can't simply add them up. Third, leakage sites are in the different blocks of the control-flow graph, which means that only one of the two leakages site may execute during the exectution.

Solution: We run the symbolic execution on the top of the execution traces. At the beginning of the exectution, each byte in the sensitive buffer is modeled with with a symbol. After that, the symbolic exectution engine interprets each instruction of the exectution traces. So every values in the registers or memory cells is modeled with a math formula.

Given a program P, k is the sensitive input. The k should be a value in a memory cell or a sequential buffer (e.g., an array). We use k_i to denote the sensitive information, where i is the index of the byte in the original buffer. We can have the following equations. The t1, t2, t3, is the temporary values during the execution.

$$t_1 = f_1(k_1, k2, ...k_n)$$

$$t_2 = f_2(k1, k2, ...k_n)$$

$$t_3 = f_3(k1, k2, ...k_n)$$

...

$$t_m = f_m(k1, k2, ...k_n)$$

After that, we model each potential leakage sites as a math formulas.

The attacker can retrieve the sensitive information by observing the different patterns in control-flows and data access when the program process different sensitive information. We refer them as the secret-dependent control flow and secret-dependent data access accordingly.

4) Secret-dependent Control Flow: Here is an example of the secret-dependent control-flows. Consider the code snippet in List 1. Here the key is the confidential data. The code will have different behaviours (time, cache access) dependenting on which branch is actually executing. By observing the behaviour, the attacker can infer which branch actually executed and know some of the sensitive information. One of the famous leakage example is the square and multiply in many RSA implementations.

For example, the attacker knows the key equals to zero if he observes the code run the branch1. Because key has 256 different possibilities. The original key has lg256 = 8 bits information. If the attacker can observe the code run branch 1. Then he will knows the key equals to zero. If the code run branch 2, the attacker can infer the key doesn't equal to zero.

```
Branch 1
temp = 0xb;
0 =< key <= 256;
temp = key/2;
```

Information Leakage = -log(1/p) = -log(1/256) = 8 bits

```
Branch 2
temp != 0;
0 =< key <= 256;
temp = key/2;
```

Information Leakage = -log(255/256) bits

```
T[64]; // Lookup tables with 64 entries
index = key % 63;
temp = T[index];
// Secret-dependent memory access
```

The simple program above is an example of secret dependent memory access. Here T is a precomputed tables with sixty-four entries. Depending on the values of key, the program may access any values in the array. Those kind of code patterns may wildly exist in many crypto and media libraries.

Suppose the attackers observe the code accesses the first entry of the lookup tables. We can have the following formulas.

```
key mod 63 = 1
0 =< key <= 256
```

So the key can be one of the following values: 1 64 127 190 253

Information leakages = -log(5/256) = 5.6 bits

C. Scalability and Performance

After we transfer each potential leaks sites into logic formula. We can group several formulas together to estimate the total information leakage. One naive way is to use the Monte Carlo sampling estimate the number of input keys. With the definition 1, we can estimate the total information leakage.

However, some pre-experiments show that above approach suffers from the unberable cost, which impede its usage to detect and quantify side-channel leakages in real-world applications. We systematically analyze the performance bottlenecks of the whole process. In general, the performance suffers from the two following reasons.

- Symbolic Execution.
- The Naive Monte Carlo Sampling.

1) Symbolic Execution: Symbolic execution interprets each instruction and update the memory cells and registers with a formula that captured the sementics of the exectution. Unfortunately, the number of machine instructions are huge and the sementics of each instruction is complex. For example, the Intel Developer Manual [9] introduces more than 1000 different X86 instructions. It is tedious to manually implement the rules for every instructions.

Therefore, existing binary analysis tools [10], [11] will translate machine instructions into intermediate languages

(IR). The IR typically has fewer instructions compared to the original machine instructions. The IR layer designs, which significantly simplify the implementations, also introduce significant overhead as well [12].

Solution: We adopt the similar approach from [12] and implement the symbolic exectution directly on the top X86 instructions.

2) Monte Carlo Sampling: For an application with m bytes secret, there are total 2^{8m} possible inputs. Of the 2^{8m} possible inputs, we want the number of inputs which satisfy those formulas. Then we can use the definition /refdef to calculate the information leakage.

A Monte Carlo method for approximating the number of $|K_o|$ is to pick up M random values and check how many of them satisfy those constrains. If l values satisfy those constrains, then the approximate result is $\frac{l*2^{8m}}{M}$.

However, the number of satisfying values could be exponentially small. Consider the formula $F = k_1 = 1 \wedge k_2 = 2 \wedge k_3 = 3 \wedge k_4 = 4$, k_1, k_2, k_3 and k_4 each represent one byte in the orginal sensitive input, there is only one possible solution of 2^{32} possible values, which requres exponentially many samples to get a tight bound. The naive Monte Carlo Method also suffers from the curse of dimensionality. For example, the libjpeg libraries can transfer the image from one format into another format. One image could be 1kMB. If we take each byte in the original buffer as symbols, the formula can have at most 1024 symbols.

Solution: We adopt the Markov Chain Monte Carlo to estimate the number of possible input that satisfies the logic formula groups. The key idea is that we have one group of input that satisfies the logic formula constrains. We can also estimate the error with chebyshev inequality. We will introduce the method in the following sections.

VI. Design

In this section, we will explain the design decisions to realize TANA.

A. Trace Logging

The trace information can be logged via some emulators (e.g., QEMU) or Binary Instrumentation Tools. For our project, we write an Intel Pin Tool to record the execution traces. The trace data has the following information:

- Each instruction mnemonics and its memory address.
- The operands of each instruction and their concrete values during the runtime.
- The value of eflags register.
- The memory address and the length of the sensitive information. Most software developers stores sensitive information in an array, a variable or a buffer, which means that those data is stored in a contiguous area in the memory. We use the symbol information in the binary to track the address in the memory.

B. Instruction Level Symbolic Execution

The main purpose of the step is to generate constraints of the input sensitive information from the execution trace. If we give the target program a new input which is different from the origin input that was used to generate the execution trace but still satisfies those constraints, the new execution trace still have the same control flow and data access patterns.

The tool runs the symbolic execution on the top of the execution traces. At the beginning of the symbolic execution, the tool creates fresh symbols for each byte in the sensitive buffer. For other data in the register or memory at the beginning of the symbolic execution, we use concrete values from the runtime information collected in the previous step. During the symbolic execution for each instruction, the tool updates every variable in the memory and registers with a math formula. The formula is made up with concrete values and the input key as the symbols accumulated through the symbolic execution. For each formula, the tool will check weather it can be reduced into a concrete values (e.g., $k_1 + 12 - k_1 = 12$). If so, the tool will only use the concrete values in the following symbolic execution.

1) Verification and Optimization: We run the symbolic execution(SE) on the top of x86 instructions. In other words, we don't rely on any intermediate languages to simplify the implemetation of symbolic execution. While the implementation itself has a lot of benefits (Better performance, accurate memory model), we need to implement the symbolic execution rules for each X86 instruction. However, due to the complexity of X86, it is inevitable to make mistakes. Therefore, we verify the correctness of the SE engine during the execution. The tool will collect the runtime information (Register values, memory values) and compare them with the formula generated from the symbolic execution. Whenever the tool finishes the symbolic execution of each instruction, the tool will compare the formula for each symbol and its actual value. If the two values don't match, we check the code and fix the error. Also, if the formula doesn't contain any symbols, the tool will use the concrete value instead of symbolic execution.

2) Secret-dependent control-flows: An adversary can infer sensitive information from secret dependent control-flows. There are two kinds of control-transfer instructions: the unconditional control-transfer instructions and the conditional transfer instructions. The unconditional instructions, like CALL, JUMP, RET transfer control from one code segment location to another. Since the transfer is independent from the input sensitive information, an attacker was not able to infer any sensitive information from the control-flow. So the unconditional control-transfer doesn't leak any information based on our threat model. During the symbolic execution, we just update the register information and memory cells with new formulas accordingly.

The conditional control-flow transfer instructions, like conditional jumps, depending on CPU states, may or may not transfer control flows. For conditional jumps, the CPU will test if certain condition flag (e.g., CF = 0, ZF =1) is met and jump to the certain branches respectively. The symbolic

engine will compute the flag and represent the flag in a symbol formula. Because we are running on a symbolic execution on a execution trace, we know which branch is executed. If a conditional jump uses the CPU status flag, we will generate the constraint accordingly.

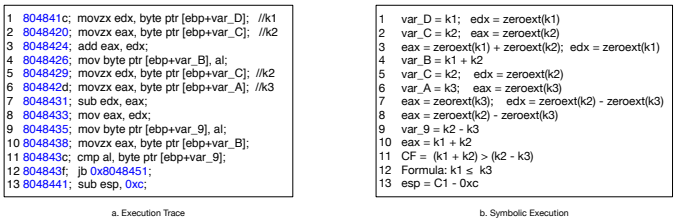


Fig. 2: The workflow of TANA

For examples,

```
...
0x0000e781      add dword [local_14h], 1
0x0000e785      cmp dword [local_14h], 4
0x0000e789      jne 0xe7df
0x0000e78b      mov dword [local_14h], 0
...
```

At the beginning of the instruction segment, the value at the address of local14h can be written as $F(\vec{K})$. At the address e785, the value will be updated with $F(\vec{K})+1$. Then the code compares the value with 4 and use the result as a conditional jump. Based on the result, we can have the following formula:

$$F(\vec{K}) + 1 = 4$$

The formula, together with the memory address (0xe789) is store as a *formula tuple (address, formula)*. Each formula tuple represents one leakage site.

3) Secret-dependent data access: Like input-dependent control-flow transfers, an adversary can also infer sensitive information from the data access pattern as well. We try to find this kind of leakages by checking every memory operand of the instruction. We generate the memory addressing formulas. As discussed before, every symbols in the formula is the input key. If the formula doesn't contain any symbols, the memory access is independent from the input sensitive information and won't leak any sensitive information according to our threat model. Otherwise, we will generate the constraint for the memory addressing. We model the memory address with a symbolic formula $F(\vec{K})$. Because we also have the concrete value of the memory address $Addr1$. Therefore, the formula can be written as:

$$F(\vec{K}) = Addr1$$

C. Markov Chain Monte Carlo Approximate Counting

From the above step VI-B, we can generate the constraints from the execution trace. The only variables in those constraints are the sensitive data. An adversary who wants to infer the sensitive data based on side-channel attacks can't observe the sensitive information directly. The adversary, however, can observe the memory access pattern of the software. Each math formula can uniquely model one leakage site.

In this section, we calculate the amount of leaked information with the definition from 1. The basic idea is to calculate $\frac{|K|}{|K^o|}$. The size of K is usually exponentially large. A naive method for approximating the result is to pick k elements from K and check how many of them are also contained in K^o. If q elements are also in K^o. In expectation, we can use $\frac{k}{q}$ to approximate the value of $\frac{|K|}{|K^o|}$. In this step, we first split the contrains tuple into multiple groups depending on the memory address. After that, we run the Markov Chain Monte Carlo to estimate the amount of leaked information.

1) Preprocessing: We apply two preprocessing steps before running the Monte Carlo sampling. First, we try to simplify those formulas by applying some normalizations rules. After that, we split those formulas into multiple groups.

The goal of the normalization is to simplify the formulas. Each formulas will be evaluated multiple times with different input during the following sampling, we would like to make those formula simpler to reduce the whole execution time. Each formula is implemented as a abstract syntax tree. We apply a series of normalization rules (e.g. key1 xor key1 = 0) to simplify the formula.

After that, we split the formula tuple into multiple groups. Each group consists of different formulas but with the same memory address. In other words, those formulas in the same group represent one leakage site. The instructions inside a loop are executed multiple times with the different item from the input buffer. We group them together to know the total information leakage.

The only symbol in the original formula is the key. An adversary who wants to infer the sensitive data based on side-channel attacks can't observe the sensitive information directly.

2) Motivation: The adversary, however, can observe the memory access pattern of the software. If the attacker can observe one leakage site, the attack is modeled as one formula. If he observes mutiple information leakage, the attack is modeled as the conjoint of those formulas. Calculating the total information leakage can be reduced to the problem of approximating the number of solutions. This is a #P problem.

One intuition way is to use the Monte Carlo method. However, as the discussion in the previous section V-C2, the number of satisfying keys could be exponentially small. Imagine an attacker who can recover one unique key after the attack, in such case, the conjoint of formula F = (f(k)) only has one solution. Also, the target program may have mutiple inputs. When the number of input symbols arises, the simple Monte Carlo may suffer from the curse of dimensionality, which means the accuracy of the result drops dramatically when the number of input symbols increases.

We adopt the Markov Chain Monte Carlo (MCMC) to estimate the number of satisfying solutions. The basic idea is to construct a Markov Chain that has the desired distribution.

Definition: Starting from here, we present the formal definition of the MCMC algorithm. First, we introduce the definition of the concept of the algorithm.

Definition 2. *An approximation scheme is an alogorithm for finding an approximation answer within a factor* $1+\epsilon$ *of the correct number of the set* K^o *with the probability of* $1-\zeta$.

Theorem VI.1. *If* $F = A_1, A_2, ..., A_n$ *is a finite collection of closed sets then* $\cup_i^n A_i$ *is a closed set.*

3) MCMC Algorithm: In the section, we present the detail of MCMC algorithm for counting the cardinality of K^o. We will fisrt present the description of the MCMC and then explain the algorithm with a concrete example.

1) Start with the concrete input $\vec{k} = (k_0, k_1, k_2, ..., k_n)$, $\vec{k}$ should be the on valid solution which satisfies the constraint $F = C_1(\vec{k}) \wedge C_2(\vec{k}) \wedge C_2(\vec{k}) \wedge ... \wedge C_m(\vec{k})$
2) for t = 1, 2, 3,..., N

VII. Implementation

We implement the TANA with 12K lines of code in C++11. It has three components, Intel Pin tool that can collect the execution trace, the intruction-level symbolic execution engine and the backend that can estimate the information leakage. The tool can also report the memory address of the leakage site. To assist the developers fix the bugs more easiliy, we also have several Python scripts that can report the leakage location in the source code with the debug information and the symbol information. A sample report can be found at the appendix.

Component	Lines of code
Trace Logging	101 LoC of C++
Symbolic Execution	11547 LoC of C++
Monte Carlo Sampling	603 LoC of C++
Others	LoC of Python

TABLE III: TANA's main components and their LoC

Our current implementation can support part of the Intel 32-bit intructions that are important in finding memory-based side-channels vulnerabilities, which include bitwise operations, control transfer, data movement and logic instructions. For other instructions the current implementation doesn't support, the tool will use the concrete values to update the registers and memory cell. Therefore, the tool may miss some leakages but won't give us any new false positives with the implementation.

VIII. Evaluation

We evaluate TANA with the real-world crypto libraries and non-crypto. For crypto libraries, we choose OpenSSL and mbedTLS, two most commonly used crypto libraries in today's software. For OpenSSL, we compile it with the option *no-asm* to disable the assembly language routines. For non-crypto libraries, we study the libjepg, a commonly used lossy library implemented by the Independent JPEG Group. We build the source code into a 32 bit ELF binary with the GCC 8.0 on Ubuntu 14.04. Although our tool can work on stripped binaries, we use the symbol information to trace back leakage sites into the source code. We use Intel Pin version 3.7 to record the execution trace.

During the evaluate, we are interested in the following aspects:

1) **Finding Leakage Sites.** How effective is TANA in identifying the memory-based side-channels vulnerabilities? How much performance overhead does the tool need to find the leakage?
2) **Leakage Sites Quantification.** Can TANA precisely report the information leakage? Is the number of leaked bits reported by TANA useful to justify the sensitive level of the side-channel vulnerability?
3) **Exsiting Leakage Sites.** Recent work has report a number of leakage sites in open source crypto libraries. But the crypto library authors don't fix them for some reasons. We use TANA to study those vulnerabilities and try to explain the reason why the author fix or not fix the side channel vulnerabilities.

A. Finding Leakage Sites

B. Leakage Sites Quantifications

C. Exsiting Leakage Sites

IX. Discussion

A. Binary code vs source code

Many existing works find side-channels vulnerabilities from source code level or intermediate languages (e.g., LLVM IR). Those approaches will have the following questions. First, many compilers can translate the operator into branches. For example, the GCC compiler will translate the ! operator into conditional branches. If the branch is secret-dependent, the attacker could learn some sensitive information. But those source-based methods will fail to detect those vulnerabilities. Second, some if else in the source code can be converted into single conditional instructions (e.g., cmov). Source-based methods will still regard them as potential leakages, which will introduce false positives.

B. X86 vs Intermediate Languages

The tool takes in an unmodified binary and the marked sensitive information as the input. The tool will first start with logging the execution trace. Then the tool will symbolizes the sensitive information into multiple symbols and start with the symbolic execution. During the symbolic execution, the tool will find any potentials leakage sites as well as the path constraints. For each leakage site, whether it is the tool will also generate the constraint. Then, the tool will split the constraints into multiple group. After that, the tool will run monte carlo sampling to estimate the total information leakages.

X. Related Work

A. Side-channel vulnerabilities detection

There are a large number of works on side-channel vulnerability detections in recent years. CacheAudit [1] uses abstract

domains to compute the overapproximation of cache-based side-channel information leakage upper bound. However, due to over approximation, the leakage given by CacheAudit can indicate the program is side-channel free if the program has zero leakage. However, it is less useful to judge the sensitive level of the side-channel leakage based on the leakage provided by CacheAudit. CacheS [13] imporves the work of CacheAudit by proposing the novel abstract domains, which only precisely track secret related code. Like CacheAudit, CacheS can't provide the information to indicate the sensitive level of side-channel vulnerabilities.

The dynamic approach, usually comes with taint analysis and symbolic execution, can perform a very precise analysis. CacheD [2] takes a concrete program execution trace and run the symbolic execution on the top of the trace to get the formula of each memory address. During the symbolic execution, every value except the sensitive key uses the concrete value. Therefore, CacheD is quite precise in term of false positives. We adopted the similar idea to model the secret-dependent memory accesses. DATA [3] detects address-based side-channel vulnerabilities by comparing execution traces under various tests.

B. Quantification

Quantitative Information Flow (QIF) aims at providing an information leakage estimate for the sensitive information given the public output. If zero bits of the information is leaked, the program is called non-interference. McCamant [14] quantify the information leaked as the network flow capacity. Phan [15] propose symbolic QIF. The goal of their work is to ensure the program is non-interference. They adopt an over approximation way of estimating the total information leakage and their method doesn't work for secret-dependent memory access side-channels. CHALICE [16] quantifies the information leakage based on Cache miss and Cache hit behaviours. But CHALICE can only work on PICA code, which limits its usage to X86 bianry. Due to complexity of the Cache model and Cartesian Bounding they use, CHALICE can only scale to small programs, which limits its usage in real-world applications.

XI. Conclusion

In this paper, we present TANA for identifying and quantifying memory-based side-channel leakages. We show that TANA is effective at finding and quantifying the side-channel leakages. With the new definition of information leakage that imitates an real side-channel attacker, the number of leaked bits is useful to justify the understand the sensitive level of side-channel vulnerabilities. The evaluation results confirm our deisgn goal and show TANA is useful to estimate the amount of leaked information in real-world applications.

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