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Abstract Model Counting: a novel approach for Quantification of Information Leaks

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ABSTRACT

We present a novel method for Quantitative Information Flow analysis. We show how the problem of computing information leakage can be viewed as an extension of the Satisfiability Modulo Theories (SMT) problem. This view enables us to develop a framework for QIF analysis based on the framework DPLL(T) used in SMT solvers. We then show that the methodology of Symbolic Execution (SE) also fits our framework. Based on these ideas, we build two QIF analysis tools: the first one employs CBMC, a bounded model checker for ANSI C, and the second one is built on top of Symbolic PathFinder, a Symbolic Executor for Java. We use these tools to quantify leaks in industrial code such as C programs from the Linux kernel, a Java tax program from the European project HATS, and anonymity protocols.

Categories and Subject Descriptors
H.1.1 [Systems and Information Theory]: Information theory; D.4.6 [Security and Protection]: Information flow controls; D.2.4 [Software/Program Verification]: Formal methods, Model checking

Keywords
Quantitative Information Flow; Model Checking; Symbolic Execution; Satisfiability Modulo Theories

1. INTRODUCTION AND BACKGROUND

Quantitative information flow analysis (QIF [14, 23]) is a rigorous approach to "measure" information leakage. The motivation for this approach is that absolute security is often not achievable and programs with "small" leaks are usually accepted as secure. QIF has attracted considerable attention in recent years and has been applied to the formal analysis of, for example, confidentiality of software [21, 5, 18, 27, 26], loss of anonymity in communication protocols [10], and leakage of information via side-channel [22, 17].

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To introduce QIF, consider the data sanitization program

\[
\text{P} = \begin{cases}
\text{base} = 8; \\
\text{if} \ (H < 16) \ \text{then} \ O = \text{base} + H; \\
\text{else} \ O = \text{base};
\end{cases}
\]

Figure 1: Data sanitization

values from 8 to 23 are possible outputs of this program. An attacker has hence available 16 possible output observations: observing outputs 9 .. 23 will know the secret \(H\) is 1 .. 15 and observing 8 will know the secret is 0 or greater than 15. Assuming the attacker has no prior knowledge of the secret \(H\) apart that is a 32 bits variable his \(a\)-priori probability of guessing the secret in one try is \(\frac{1}{2^{32}}\), and the expected probability of guessing the secret in one try after observing the outputs is:

\[
\text{log} \left( \frac{15}{2^{32}} \right) + \frac{2^{32} - 15}{2^{32}} \cdot \frac{1}{2^{32}} = \frac{15}{2^{32}} + \frac{1}{2^{32}} = \frac{16}{2^{32}}
\]

We can measure the leakage of the program as the difference (of the \(-\log (\text{base} 2)\)) between the probability of guessing the secret before and after observing the outputs of the program; in this case:

\[
-\log \left( \frac{1}{2^{32}} \right) - \left( -\log \left( \frac{16}{2^{32}} \right) \right) = \log(16) = 4
\]

The fact that \(\log(16) = \log (\text{number of output observations})\) is not a coincidence. In fact a fundamental QIF result (the channel capacity theorem [24, 33]) shows that leakage for a program is always less or equal to the log of the number of observables of the program. More importantly the theorem holds if we consider not only the above notion of leakage based on the probability of guessing the secret [33] but also if we consider the notion of leakage based on information theory measuring the number of bits leaked [14].

For these reasons counting the number of observables is the basis of state-of-the-art QIF analysis, e.g., [18, 26, 22, 21], and also the basis for this work. The channel capacity theorem also justifies the following:

Definition 1. Given a program \(P\), QIF is the problem of counting \(N\), the number of possible outputs of \(P\).

However the problem of an automated QIF analysis is still very challenging. A simpler problem, called bounding QIF, is considered in [34, 18]: deciding if a program \(P\) leaks less than a constant \(q\). In previous work, Yasuoka and Terauchi
have proved that bounding QIF is not a $k$-safety problem for any $k$ [34]. Cerny et al. then proved that in the case of Shannon entropy, bounding QIF is PSPACE-complete [12]. So QIF and bounding QIF remain a huge challenge.

1.1 Overview and Contributions

In order to better frame the contributions of this paper let us consider again the program $P$ in Figure 1. In the computer memory, $O$ is stored as a bit vector $b_1, b_2, b_3, b_4, b_5$ such that the first 27 bits, $(b_1, b_2, b_3, b_4)$, are 0 (otherwise $O$ will exceed 23) and the last 5 bits range from 01000 to 10111.

Suppose we have a logical formula $\varphi_P$ that describes the behaviour of $P$ which contains a set of variables $p_1, p_2, ..., p_{32}$ representing the bits of the output $O$. A model of $\varphi_P$ then provides a truth assignment for the $p_i$ which corresponds to a concrete value of the output $O$. In this way, the problem of counting all possible outputs, is reduced to the model counting problem on the logical formula $\varphi_P$. We name this problem abstract model counting, from the traditional model counting (#SAT) problem.

In summary, we introduce a theory-based technique which provides a dramatic improvement on state-of-the-art QIF analysis implementations. On the theoretical side, this work establishes a connection between fundamental verification algorithms and QIF. This connection is exploited to mitigate the state explosion problem by developing a novel approach for QIF based on SMT. More specific contributions are:

1. Introduction of a new research problem, #SMT, and its applications to QIF and Symbolic Execution [20].
2. A framework, called #DPLL($T$), to build a solver for #SMT-based QIF.
3. The methodology of Symbolic Execution re-casted as #DPLL($T$).
4. Two prototyping tools for QIF analysis: sqifc built on top of CBMC [15] and jpf-qif built on top of Symbolic PathFinder [32].
5. Analysis of complex code, including new vulnerabilities from the National Vulnerability Database of the US government [2] and anonymity protocols.

The rest of the paper is organized as follows: we describe the #SMT problem and our approach to QIF in Section 2. To illustrate the approach, we provide case studies of real-world applications in Section 3. Related work is mentioned in Section 4. Section 5 concludes our work.

2. ABSTRACT MODEL COUNTING

Before introducing our approach, Symbolic QIF (or SQIF), we recall the SMT problem, and define the new problem #SMT.

Satisfiability Modulo Theories (SMT) is the problem of checking the satisfiability of logical formulas over one or more first-order theories $T$. Boolean abstraction of an SMT formula $\varphi$, denoted by $BA(\varphi)$, is a bijective function that maps Boolean atoms into themselves and theory atoms (or $T$-atoms) into fresh Boolean atoms. For example, below is a SMT formula $\varphi$ w.r.t. the theory of Linear Arithmetic and its Boolean abstraction:

$$\varphi := \neg(x + y > 1) \lor A_1 \quad BA(\varphi) := \{\neg B_1 \lor A_1\}$$

$$\land \{\{x + y > 1\} \lor \neg A_2\} \land \{B_1 \lor \neg A_2\} \land \{-A_1 \lor (y - z < 7)\} \land \{-A_3 \lor B_2\}$$

We extend the traditional SMT problem to define a new research problem, namely #SMT:

**Definition 2.** Given a formula $\varphi$ w.r.t. combinations of background theories $T$ and its Boolean abstraction $BA(\varphi)$, propositional abstract model counting or #SMT is the problem of computing the number of models of $BA(\varphi)$ which are consistent with $\varphi$. Such models of $BA(\varphi)$ are also called abstract models of $\varphi$.

Note that most SMT theories permit an infinite number of models, but #SMT is always a finite number. Note also that the result of #SMT depends on the syntax of the formula, i.e. in our context the program syntax. For instance, the two formulas $\varphi_1, \varphi_2$ as follows are equivalent but will have different results in #SMT: $\varphi_1 = (x > 0) \lor (x < 0)$ and $\varphi_2 = (x = 0)$.

State-of-the-art SMT solvers are in general the integration of two components: (i) an enumerator integrating a SAT solver enumerates truth assignments satisfying the Boolean abstraction of the input formula; (ii) $T$-solvers validate the consistency w.r.t. theories $T$ of the (partial) assignment produced by the SAT solver. Naturally, an SMT solver can be extended into a #SMT solver by replacing the SAT solver with a #SAT solver that can explicitly enumerate all models.

2.1 Symbolic QIF as a #SMT problem

The key idea behind SQIF is that instead of checking every concrete value one by one, we process multiple values at a time. To this aim, we need a representation denoting a set of values. We consider a set of atomic propositions $\Phi := \{p_1, p_2, ..., p_{32}\}$, in which each $p_i$ corresponds to the bit $b_i$ of the output $O$. For example the proposition $p_1 \land \neg p_2$ represents a family of sets representing up to $2^{32-2} = 24$ concrete values: all the bit configurations over $M$ bits where the first bit is 1 and the second bit is 0.

```plaintext
for all output bits $b_i$, $1 \leq i \leq M$
do
if ($b_i = 1$) then
$p_i = True$
else
$p_i = False$
end if
end for
```

Figure 2: Symbolic representation

Obviously, without any constraints $\Phi$ can represent up to $2^M$ possible values. With the constraints on the output $O$ imposed by the program $P$, the number of models of $\Phi$ is down from $2^M$ to a number $N$ that we need to count. To generate the formula of these constraints: the program $P$, to which the code in Figure 2 has been appended at the end, is first transformed into a logical formula $\varphi_P$ w.r.t. theories $T$, e.g. by translating statements into Static Single Assignment (SSA) form. Once $P$ is encoded as a logical formula $\varphi_P$, then we can apply model checking on $P$ to verify the satisfiability of $\varphi_P$. In other words, a model checker like CBMC is used as a $T$-solver.
Program $\rightarrow$ Logical formula

Model checker $\rightarrow$ T-solver

If one accepts the view that each $p_i$ is a Boolean abstraction of the T-atom expressing the constraints on bit $b_i$, then the QIF problem of counting $N$ can be viewed as a #SMT problem. In other words, with this view the QIF analysis (Definition 1) is a #SMT problem.

The transformation from programs to logical formulas is also exactly what bounded model checkers like CBMC do: once a program is converted into a logical formula then its satisfiability is checked with a SAT solver or an SMT solver. We however can also use non SAT-based model checkers, e.g. Java PathFinder (JPF) [1], as a T-solver. Our approach does not depend on a programming language or the type of model checker.

At this point we have defined the notation of a symbolic representation $\Phi$ of the state space of the output $O$. In the next section, we will describe a DPLL-based framework to systematically explore $\Phi$.

### 2.2 A DPLL($T$) for QIF

The first practical approach for #SAT is an extension of DPLL [11] that enumerates all models. Modern #SAT solvers, e.g. RelSat [9] and c2d [16], are more efficient thanks to smarter approaches that exploit the structure of solvers, e.g. RelSat [9] and c2d [16], are more efficient than standard approaches that explicitly enumerate of DPLL [11] that enumerates all models. Modern #SAT solvers, e.g. RelSat [9] and c2d [16], are more efficient thanks to smarter approaches that exploit the structure of the clauses and avoid explicitly enumerating models. In the context of #SMT, however, explicit enumeration of abstract models is necessary since we need to check the consistency of each abstract model w.r.t. the background theory $T$. The Symbolic QIF framework we propose here is a DPLL($T$) tailored for QIF, by combining a simple DPLL-based #SAT solver and a T-solver. Hence, this variant of DPLL($T$) is a #SMT solver in the context of QIF.

A high level framework to explore the state-space and quantify the leaks of confidential data is described by the procedures SymbolicQIF and SymCount in Figure 3 and 4.

```plaintext
function SYMBOLICQIF($\Phi, \varphi_P$)  
  $\Psi = \epsilon, pc = \epsilon, N = 0, i = 1$
  EarlyPrunning($\Phi$)
  return $\Psi, \log_2(N)$
end function

function SymCount($\Phi, \Psi, \varphi_P, N, pc, i$)  
  if ($N > 2^i$) return Insecure
  end if
  Extract $p_i$ from $\Phi$
  $pc_1 \leftarrow pc \land p_i$
  if ($T$-solver($\varphi_P, pc_1$)) then
    if ($i == M$) then
      $\Psi \leftarrow \Psi \cup \{pc_1\}$
      $N \leftarrow N + 1$
    end if
  end if
  else
    SymCount($\Phi, \Psi, \varphi_P, N, pc_1, i + 1$)
  end if
end function

Figure 3: Symbolic QIF analysis

$\Phi, \Psi, \varphi_P$ and $N$ are passed by reference, while $pc$ and $i$ are passed by value. $\Phi$ is the symbolic representation of the output described in the previous section, $\varphi_P$ is the formula representing the program $P$ and $\Psi$ is the set of models of $\varphi_P$. $N$ is the cardinality of $\Psi$, and the procedure SymbolicQIF returns $\log_2(N)$ as the channel capacity. $M$ is the size of the output data type, e.g. $M = 32$ if $O$ is a 32-bit integer, and $i$ is the depth of the recursive call. The parameter $pc$ is a partial assignment of $\Phi$, it is incrementally updated when the search progresses. In SymCount, $T$-solver($\varphi_P, pc$) means the $T$-solver is called to check if there is a model of $\varphi_P$ where $pc$ is (assigned to) True.

We illustrate the algorithm SymCount by running it on a simple example (we ignore temporarily lines 2 and 3 that will be clarified in section 2.4). Consider again the case study of the data sanitation program in Figure 1. Only integer values from 8 to 23 are possible outputs of this program, which means the number of possible outputs is $N = 16$. At the beginning, all variables are initialised as in Figure 3, which means the number of possible outputs is $N = 16$.

Figure 5: Partial exploration path of SQIF for the data sanitisation program from Figure 1.
A model checking tool like JPF or CBMC can be used as a T-solver to verify this assertion and it will return True if the assertion fails, and False otherwise. In this example, the T-solver would return True since \( p_1 \) stands for “first bit is 1” and all odd values from 9 to 23 are possible outputs satisfying the condition \( p_2 \). Hence, SQIF proceeds by calling SymCount with \( i = 2 \). Similarly, the procedure progresses until calling SymCount with \( i = 5 \), which means it needs to verify:

assert !(\( p_1 \land p_2 \land p_3 \land p_4 \land p_5 \));

This time the T-solver would return False, since \( p_1 \land p_2 \land p_3 \land p_4 \land p_5 \) represents a set of outputs of which each element is at least \( 2^0 + 2^1 + \ldots + 2^4 = 31 \), while the possible range of \( O \) is only from 8 to 23. For a program with an output of 32-bits, by using EarlyPrunning, SQIF trims a set of 2\(^{27}\) concrete values represented by the family of sets:

\[
\{ \Phi := \{ p_1, p_2, \ldots, p_{32} \} : p_1 \land p_2 \land p_3 \land p_4 \land p_5 \}\]

This is how the state-space explosion problem is mitigated.

At the depth \( i = 5 \) as above, if SQIF takes the path of \( \neg p_5 \) from line 14, then the T-solver returns False (\( O = 15 \) is one of the models). Hence, the procedure continues with \( i = 6 \), and from this point until \( i = 32 \), only the path of \( \neg p_5 \) is SAT. At \( i = 32 \), SQIF finds a full path 00.011111 which represents an output \( O = 15 \). This path is added to \( \Psi \), and SQIF increases \( N \). Finally, at the end of the method SymbolicQIF, we have \( \Psi = \{ 8, 9, \ldots, 23 \} \) and \( N = 16 \), thus we can conclude that the data sanitization program in Figure 1 looks at most 4 bits.

The method EarlyPruning implements the idea that if \( p_1 \) is unsatisfiable, then \( p_1 \land C \) is also unsatisfiable for any \( C \). Therefore, at the beginning of the SymbolicQIF, all \( p_i \) are checked for satisfiability, and the results are stored for later use. We note that EarlyPruning speeds up SymbolicQIF dramatically when the number of possible models (outputs of the program) is small.

We have developed a prototyping tool for QIF analysis of C programs, sqifc built on top of CBMC.

### 2.3 Symbolic Execution as #DPLL(T)

Symbolic Execution (SE) [20] is a powerful technique, widely used in many domains of application such as test data generation, partial verification, symbolic debugging, and program reduction. Here we argue that:

Suppose a program is encoded into a logical formula then a Symbolic Executor can be viewed as a #SMT solver for this formula.

Intuitively, if we see a program as a logical formula, then a concrete execution of the program corresponds to a model of that formula. A symbolic path, which represents a set of concrete executions, can be viewed as corresponding to the Boolean abstraction of the set of models. Thus, a Symbolic Executor, returning all symbolic paths of a program, can be viewed as a #SMT solver.

Program \( \rightarrow \) Logical formula

Concrete execution \( \rightarrow \) Model of the formula

Symbolic path \( \rightarrow \) Boolean abstraction of models

**Example 1.** To illustrate the idea, consider a simple C program as follows:

```c
if (x > 1) { y = x < 5 ? x + 10 : x;} else y = 0;
```

We denote the propositional variables: \( C_1 \) as \((x > 1)\), \( C_2 \) as \((x < 5)\), \( A_1 \) as \((y_1 = x + 10)\), \( A_2 \) as \((y_2 = x)\), and \( A_3 \) as \((y_3 = 0)\). In this way, the program can be viewed as a Static Single Assignment-like (SSA) logical formula:

\[
(C_1 \rightarrow ((C_2 \rightarrow A_1) \land (\neg C_2 \rightarrow A_2))) \land (\neg C_1 \rightarrow A_3)
\]

This is a formula modulo the theory of linear arithmetic. In the Boolean abstraction of the formula, \( A_1, A_2 \) and \( A_3 \) are pure literals and can be removed. The formula has hence three models that can be written as:

\[
\{ C_1 \land C_2, C_1 \land \neg C_2, \neg C_1 \}
\]

This is also the set of possible symbolic paths generated by running SE on the program.

1: function SymEx\((P, \sigma, pc, l)\)
2: Execute assignment statements, update \( \sigma \)
3: if \((l = EOF)\) then
4: \( \Psi \leftarrow \Psi \cup \{pc\} \)
5: \( \Sigma \leftarrow \Sigma \cup \{\sigma\} \)
6: return
7: end if
8: Extract \( \{c, l, l_T, l_\perp\} \) from if-statement
9: if \((T\text{-solver}(pc \leftarrow c))\) then
10: SymEx\((P, \sigma, pc, l_T)\)
11: else if \((T\text{-solver}(pc \leftarrow \neg c))\) then
12: SymEx\((P, \sigma, pc, l_\perp)\)
13: else
14: \( pc_1 \leftarrow pc \land c \)
15: if \((T\text{-solver}(pc_1))\) then
16: SymEx\((P, \sigma, pc_1, l_T)\)
17: end if
18: \( pc_2 \leftarrow pc \land \neg c \)
19: if \((T\text{-solver}(pc_2))\) then
20: SymEx\((P, \sigma, pc_2, l_\perp)\)
21: end if
22: end if
23: end function

**Figure 6: Symbolic Execution**

The above example suggests we can see SE as #SMT solver, we will now derive SE in the #DPLL(T) framework. Let us consider a program in SSA form and consisting of only assignment statements and conditionals. Tools such as CBMC and Soot [1] transform ANSI C and Java programs into SSA to verify properties.

![Figure 7: Partial exploration path of SQIF-SE for the data sanitisation program from Figure 1.](image-url)
The algorithm of SE is depicted in Figure 6. Here σ is a symbolic environment, i.e. a map from program variables to formulas over symbolic inputs. The parameter pc holds the current path condition. At the end of the procedure, Ψ will be the set of all path conditions and Σ will be the set of all final symbolic environments, one for each path condition. Statements in the program P are identified by their program location l. For a conditional statement if (c) I else I’, symbols l and l’ denote the locations of the first statements in I and I’ respectively. Notice that in SymEx lines 9 to 12 can be viewed as T-propagation, and lines 14 to 21 can be viewed as splitting in DPLL(T) [28].

In SymEx T-solver(pc + c) calls the solver to check whether c is a consequence of pc and T-solver(pc) calls the solver to check whether pc is satisfiable.

We believe that the insight of SE as #DPLL(T) paves the way for the development of efficient Symbolic Executors, by exploiting techniques that have been successful in SMT such as non-chronological backtracking and clause learning [31].

### 2.3.1 SQIF by Symbolic Execution:

With the view of SE as #DPLL(T), we are able to make a Symbolic Executor work as SymbolicQIF with little effort. The key idea here is to enumerate all concrete values from symbolic executions.

For a program P that takes symbolic inputs i1, i2,...,in, and produces an output O, the result of running SE on P is as follows:

\[
O = \begin{cases}
  f_1(i_1, i_2, ..., i_n) & \text{if } pc_1 \\
  f_2(i_1, i_2, ..., i_n) & \text{if } pc_2 \\
  \vdots & \\
  f_\beta(i_1, i_2, ..., i_n) & \text{if } pc_\beta
\end{cases}
\]

where \(f_1, f_2,...,f_\beta\) are formulas over symbolic inputs \(i_1, i_2,...,i_n\), \(pc_1, pc_2,..., pc_\beta\) are the path conditions. Notice \(f_i\) expresses a symbolic final value for \(O\), i.e. in terms of SymEx instead of \(f_i(i_1, i_2,...,i_n)\) we could write \(\sigma_i(O)\) for \(\sigma_i \in \Sigma\). The following proposition was proved by King [20]:

**Proposition 1.**

\[\forall i, j \in [1, \beta] \land i \neq j, pc_i \land pc_j = \bot\]

which means that path conditions are mutually exclusive.

**Definition 3.** For a path condition \(pc_i\) obtained from SE, the concretization set of \(pc_i\), denoted \(\mathcal{CS}(pc_i)\), is the set of all concrete values of output \(O\) that can be reached by executing the program following \(pc_i\).

Consider again the Example 1 in which there are three path conditions: \(pc_1 = C_1 \lor C_2, pc_2 = C_1 \land \neg C_2, pc_3 = \neg C_1\). The corresponding concretization sets of these path conditions are: \(\mathcal{CS}(pc_1) = \{12, 14\}, \mathcal{CS}(pc_2) = \{5, 2^M\}, \mathcal{CS}(pc_3) = \{0\}\), where \(M\) is the number of bits of the variable \(x\). The set of all possible values of output \(O\) is formed by the union of concretization sets of all paths, and thus:

\[N = \bigcup_{i=1}^{\beta} \mathcal{CS}(pc_i)\]

The set \(\mathcal{CS}(pc_i)\) can be computed by inserting the code in Figure 2 at the end of the program and run SE: we add \(M\) conditions, each one tests whether bit \(b_i\) of the output \(O\) is 0 or 1. These \(M\) conditions test all the bits of the output \(O\). Exploring all possible combinations of these conditions leads to enumerating all possible values of \(O\). We denote by SQIF-SE the implementation of SQIF using SE. A partial exploration path of SQIF-SE is described as in Figure 7. SE as implemented by Symbolic PathFinder (SPF) returns a concrete value for each possible path. The number of distinct concrete values is the \(N\) that we need to count.

SQIF-SE is implemented into a prototyping tool \(jpf-qif\) built on top of SPF. The tool works on Java programs.

### 2.4 Soundness and Completeness

By soundness of the SQIF approach we mean that given \(\Psi, \log_2(N)\) returned by SymbolicQIF(\(\Phi, \varphi_F\)), each element of \(\Psi\) is a model of \(\varphi_F\) i.e. corresponds to a possible value of the output of the program \(P\). By completeness of SQIF, we mean that \(\Psi\) is the set of all models of \(\varphi_F\) i.e. all values of the output of \(P\).

**Theorem 1.** Given a sound (resp. complete) T-solver the SQIF approach is sound (resp. complete) i.e. SymCount solves the QIF problem (Definition 1).

**Proof Sketch 1.** The SQIF algorithm as described in Figure 4 is based on DPLL which itself is a depth-first search procedure. As the search space is a binary tree with bounded depth \(M\), the number of bits of the output, the depth-first search procedure is complete. The soundness of SQIF is guaranteed by the soundness of the T-solver, i.e. model checker.

In reality T-solvers are only complete in particular domains. Moreover, even with sound and complete T-solvers, a large leak requires an exponential number of calls to the T-solver and so in practice SQIF is complete only for programs with small leaks. SQIF-SE relies on a Symbolic Executor, and hence it is complete in programs with a bounded model of runtime behaviour, which means programs have no recursion or unbounded loops. These are well-known issues in SE and handling them is orthogonal to our work. Since our tools are based on bounded model checker and bounded SE, we choose to analyse only bounded programs. Notice however that Theorem 1 holds for general T-solvers.

Because of these practical issues about completeness, it has been proposed to shift the focus from the question “How much does it leak?” to the simpler quantitative question “Does it leak more than \(k\)?” [18, 34]. This approach not only makes the problem easier to analyze, but it is also more intuitive in term of security, because the user policy, i.e. threshold \(k\), is encoded in the analysis. The ultimate goal of security analysis is to determine whether a program is secure or insecure. As discussed in the previous section, the goal of QIF is to relax security policy from non-interference to an acceptable threshold \(k\) bits of interference, so that we can tolerate “small” leak, and accept more programs as secure. The SQIF approach can also be used in the same way: with a user policy \(k\), if SQIF finds out more than \(K = 2^k\) possible outputs, we can stop the procedure and conclude that the program is insecure. This is the meaning of lines 2 and 3 of function SymCount in Figure 4.

A straightforward consequence of the Theorem 1 is that, assuming a sound T-solver, given a user policy \(k\), SymCount never returns secure for a program leaking more than \(k\) bits. This can be formally expressed as:

**Corollary 1.** SQIF is sound w.r.t a user policy \(k\).
3. CASE STUDIES

Only few papers present QIF static code analysis of real-world applications: examples are [18], [22] and the more recent [21]. Of these three approaches, [22] uses a different attacker model, namely cache side-channels and so is not directly comparable with our approach. The other two, [18] and [21], use the same attacker model as we do but are at the moment both restricted to C programs, and hence only comparable to sqifc. We will concentrate on [18], to which we refer as selfcomp, because it is based on the well-known concept of self-composition [7]. sqifc is compared to [21] in section 3.7. For the analysis of anonymity protocols, we compare sqifc against QUAIL [3, 10], a state-of-the-art quantitative analyser for probabilistic programs. The case studies broadly fall in three categories:

- the first category, consisting of case studies from the National Vulnerability Database of the US government [2], is aimed to demonstrate how our analysis is able to deal with complex C-code,
- the case studies CRC and Tax show the applicability to quantify leakage in applications which leak by design, and
- the case studies Grade and Dining cryptos protocols show how our technique, even if it is unable to analyse probabilistic programs, is able to computing channel capacity for anonymity protocols.

The experiments are conducted on a desktop machine with Intel Core i5 3.3GHz and 8GB of memory.

3.1 CVE-2011-2208

This case study is an example of a program that leaks information when the attacker can control the public input. It is taken from the National Vulnerability Database (NVD) of the US government [2], and it is released on 13/06/2012. The system call osf_getdomainname, depicted in Figure 8, in

In order to quantify the information leakage caused by this vulnerability, we chose the thresholds of security policy \( K = 64 \) and \( K = 256 \), which means the program is secure if it leaks less than 6 and 8 bits respectively. After the times in Figure 11, sqifc and selfcomp conclude that the program is insecure. We then apply the patch provided for this vulnerability, and run sqifc again. This time, sqifc found only one possible value for name, which means a leak of zero bit. Hence, we prove that the patch fixed the leak.

3.2 CVE-2011-1078

This case study is also taken from NVD, and it is released on 21/06/2012. The function sco_sock_getsockopt_old in the Linux kernel before 2.6.39, depicted in Figure 9, leaks sensitive information from kernel memory. As in line 24, cinfo is copied to the user. Although its total size is 5 bytes, and all bytes are correctly assigned, when compiled it includes an additional padding byte for alignment purposes. This padding byte is not zeroed out, and hence it contains kernel memory, and is leaked to the user. Results of the analysis for \( K = 8 \) and \( K = 64 \), are shown in Figure 11.

3.3 Cyclic Redundancy Check

The program in Figure 10 performs Cyclic Redundancy Check (CRC) and shifts right the result sft bits. We also have a Java version of the program to test with jpf-qif. We quantify the amount of information of the confidential input ch revealed by observing the output of function GetCRC8. We analyse this program with sqifc, jpf-qif and selfcomp for sft values of 3 and 5 giving a maximum leakage for this program of 5 (selfcomp times out on this case) and 3 bits respectively which is consistent with the design of the program. Results of the analysis for are shown in Figure 11. In the case value of sft is 5, i.e. \( K = 8 \), selfcomp is faster as the state-space is still small enough, and selfcomp requires only one call to CBMC. When sft = 3, i.e. \( K = 32 \), the state-space explosion makes selfcomp fail to solve. SQIF

Figure 9: net/bluetooth/sco.c

Figure 8: arch/alpha/kernel/osf.sysc

Figure 10: net/bluetooth/sco.c
We denote $S_1, \ldots, S_k$ be the $k$ students arranged in a ring, each one is given a secret grade $g_i$ between 0 and $m - 1$. To compute the sum of $g_i$ without disclosing them, the students produce $k$ random numbers between 0 and $n = (m - 1)k + 1$ such that the number $r_i$ is known only to the students $S_i$ and $S(i+1)\%k$. Each student $s_i$ then outputs a number $d_i = g_i + r_i - F(i+1)\%m$ and the sum of all grades is equivalent to the sum of the outputs modulo $n$.
### 3.7 Optimizing SymCount

One source of inefficiency in the implementation of sqifc is that: in each call to CBMC, the transformation from the source code to the logical formula \( \varphi_F \) is recomputed. This can be very costly when the program is large or many calls to CBMC are needed. A simple optimisation to tackle this problem is to use CBMC to compute \( \varphi_F \) once and for all, and then use a SAT or SMT solver to check \( \varphi_F \) together with the appropriate assertion at line 6 or 15 of SymCount. We denote the resulting implementation \( \text{sqifc}^+ \): it analyses CRC(8) in 0.289 and CRC(32) in 0.475 seconds respectively: an average improvement well over 1000% over \( \text{sqifc} \).

We believe the performance of \( \text{sqifc}^+ \) is comparable to the technique in [21] for programs with small leaks but it is outperformed when analysing programs with large leaks (a precise comparison is not possible as all but one programs in [21] have large leaks), however we don’t see this as a big issue: the main point of QIF is to determine whether a program leaks a small amount and hence can be considered a secure program, and while the meaning of “small leak” is context dependent it is difficult to see contexts where leaks much larger than 10 bits can be considered small.

### 4. RELATED WORK

Meng and Smith introduce an approximate technique to calculate an upper bound on channel capacity in [26]. The authors’ implementation of the method is largely manual, and we proposed an automation for it in [30]. While the work of Meng and Smith is very inspiring, the technique can be very imprecise, for example when the leaks are sparse in the state space. Moreover, the user policy is not encoded in the analysis which makes it infeasible when the leaks are not small. Take an example of a program that leaks all 32 bits, it needs to make another \( 496 \times 4 \) = 1984 calls to STP solver to determine that all bits are not small. Take an example of a program that leaks all 32 bits, it needs to make another \( 496 \times 4 \) = 1984 calls to STP solver to determine that all bits are not small.

The first automated method for QIF was proposed by Backes et al. [5]. The method can be divided into two stages: first, it employs model checking to compute an equivalence relation \( \mathcal{R} \) on the set of confidential inputs w.r.t. observable outputs; secondly, if this relation \( \mathcal{R} \) can be represented by a system of linear integer inequalities \( \mathbb{A} x \geq b \), which means it is a bounded integer polytope, then a variant of Barvinok’s algorithm [8] can be used to count the number of integer polytopes.
solutions of $R$. While this work is important as the first effort on automation of QIF analysis, it is not clear however how this approach can be applied to real-world programs because of, for example, bit-wise operators in the CRC case study or non-linear relations and so on.

Closer to our work is the paper of selfcomp [18] discussed in the previous section. However, as already outlined their approach to address the question "Does it leak more than $k$?" is quite different from ours. Köpf et al. [22] also apply QIF to real-world applications, i.e. leakage of cache side-channels; their technique is based on abstract interpretation and hence not based on bounded models. Because of this however they over-approximate channel capacity.

A preliminary version of the algorithm SymCount has been presented in a workshop [30]. In our previous work, we also used Symbolic Execution for qualitative information flow analysis [29]. A recent paper [21] explores QIF in a pure logical framework. The approach is powerful and elegant, however it is more limited when compared to our approach as it relies on the solver to generate models whereas our approach can use any solver instead. For example we can analyse Java by using JPF as a solver for bytecode even if JPF doesn’t generate a model in the sense of [21].

McCamant and Ernst released FlowCheck [25], a tool for security testing based on dynamic taint analysis. What FlowCheck measures is the number of tainted bits, not an information-theoretic bound, so it is significantly different from our approach. Another tool is described in [27], it is able to analyse large programs using the notion of channel capacity in the context of dynamic taint analysis, while our approach is based on verification techniques. In this sense, our work comes with stronger theoretical guarantees.

5. CONCLUSION AND FUTURE WORK

We introduce Abstract Model Counting, a novel approach based on SMT for the quantification of information leaks for real-world applications. Although our implementation is far from being optimised, it drastically outperforms the existing technique based on self-composition. Our approach is applicable to programs with difficult data structures such as pointers, and to Java bytecode.

An original contribution of this work on the theoretical side is: the establishment of connections between measuring confidentiality leaks and fundamental verification algorithms like Symbolic Execution, SMT solvers and DPLL. As a first consequence of these connections we have developed new QIF techniques implemented on two prototype tools for C and Java respectively. We have demonstrated the potential of these tools on C and Java code and argued that while measuring large leaks remains an infeasible task, the most interesting case, i.e. verifying whether a program only leaks a small amount of the secret may be dramatically improved by the techniques here introduced.

An immediate direction for investigation is: instead of dealing with programs as hidden formulas as in this paper, we may view it as an SMT formula w.r.t. the theory of Quantified Bit-Vector, and work directly with the formula. Other interesting directions include to explore the possibility of analysing anonymity protocols under specific probability distributions.

6. ACKNOWLEDGEMENTS:

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7. REFERENCES

[8] Barvinok, A. I. A polynomial time algorithm for counting integral points in polyhedra when the

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Figure 15: Elapsed time in seconds of QUAIL

(d) Students

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Figure 16: Elapsed time in seconds of sqifc

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Figure 17: The dining cryptos protocol analysed by sqifc
Clarke, E., Kroening, D., and Lerda, F.

Clark, D., Hunt, S., and Malacaria, P.

Darwiche, A.

Doychev, G., Feld, D., Köpf, B., Mauborgne, K., Miehlsbach, A. S., Ouaknine, J., Heusser, J., and Malacaria, P.

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Birnbaum, E., and Lozinskii, E. L.

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