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Symbolic Quantitative Information Flow

Quoc-Sang Phan, Pasquale Malacaria
Queen Mary University of London

Oksana Tkachuk, Corina S. Păsăreanu
NASA Ames Research Center

ABSTRACT
Quantitative Information Flow (QIF) is a powerful approach to quantify leaks of confidential information in a software system. Here we present a novel method that precisely quantifies information leaks. In order to mitigate the state-space explosion problem, we propose a symbolic representation of data, and a general SMT-based framework to explore systematically the state space. Symbolic Execution fits well with our framework, so we implement a method of QIF analysis employing Symbolic Execution.

We develop our method as a prototype tool that can perform QIF analysis for a software system developed in Java. The tool is built on top of Java Pathfinder, an open source model checking platform, and it is the first tool in the field to support information-theoretic QIF analysis.

Keywords
Algorithms, Security, Verification

1. INTRODUCTION
Protecting confidential data is always a big concern when building a software system. Intuitively, a system is considered to be secure if confidential data cannot be inferred by an attacker through his observations of the system. This intuitive policy is formalized as non-interference: an observable output $O$ is not affected by any confidential data $H$. Non-interference has been widely studied during the last four decades [14]. Although satisfying non-interference is a sound guarantee for a system to be secure, this classifies many intuitively secure programs as insecure. Consider for example the following password checking program:

```java
if (H == L) accept else reject
```

The program takes a public input $L$ controlled by the user, grants access if $L$ is equal to the confidential password $H$, and rejects otherwise. With a strong enough password, this program is intuitively secure. However, it violates non-interference since the result of “accept” or “reject” depends on the confidential data $H$. Therefore, qualitative methods would classify the program as insecure. This is the main weakness of qualitative methods, which makes the analysis imprecise for a large class of programs.

Quantitative Information Flow (QIF) has been developed to address the limitation of qualitative information flow [7, 8]. The key idea of QIF is simple: instead of accepting only programs with “zero interference” (non-interference) as secure, we quantify the interference and accept programs with “small” interference as secure. To illustrate the concept of QIF, we consider an attacker model in which an attacker observes the program $P$ and tries to infer the value of the confidential data $H$ of the program by observing the output $O$ of $P$. Suppose we have a function $F$ measuring the attacker’s knowledge of the secret. Initially, the knowledge of $H$ is $F(H)$; we note the attacker’s knowledge about $H$ after observing the output $O$ by $F(H|O)$. We then define leakage as the difference between the a priori and a posteriori attacker’s knowledge, i.e.

$$\Delta_F(H) = F(H) - F(H|O)$$

If the program satisfies non-interference, observing $O$ will not affect the attacker’s knowledge of $H$:

$$F(H|O) = F(H) \text{ thus } \Delta_F(H) = 0$$

In general the security policy is relaxed from 0 to an acceptable threshold $k$. This enables QIF to tolerate small leaks and accept more programs as secure.

The function $F$ is in general based on Information Theory. A natural choice for $F$, when interpreting knowledge as information, is Shannon entropy. An alternative, if one views knowledge in terms of the probability of guessing the confidential data in one try, is to choose $F$ as Renyi’s min-entropy [15]. Alternatively, $F$ can also be guessing entropy [11], if knowledge is interpreted as the expected number of guesses to reveal the confidential data. Readers who are interested in algebraic foundations of QIF may consult [9, 15] for more details.

2. BACKGROUND
There is always a trade-off between precision and computational complexity, and this is the case for QIF. While providing more precision in reasoning about security, QIF also introduces more complexity than traditional qualita-
tive methods. It is impractical to perform QIF analysis manually as in [3] for real-world applications. That leads to the need of automated, possibly approximated, methods for QIF. Previous work [10, 15] has proved that:

$$\Delta_F(H) \leq \log_2(N)$$

(1)

with $N$ as the number of possible values for the output $O$. This result is important, since it frees us from the tedious and expensive task of calculating various (conditional) probabilities on software data. Thus, the problem of QIF analysis is reduced to the problem of counting $N$. From now on, when we talk about "precise" or "approximate" QIF analysis, we also mean precise or approximate calculation of $N$, since precise calculation of $\Delta_F(H)$ is almost impossible.

However, even if the result in [1] reduces the complexity of a QIF analysis, the problem of an automated analysis is far from being solved: counting the number of possible outputs $N$ remains a huge challenge. Suppose a program $P$ takes $k$ inputs $I_1, I_2, \ldots, I_k$ and produces an output $O$. $P$ can be viewed as a function:

$$f : D_1 \times D_2 \times \cdots \times D_k \rightarrow D_o$$

where $D_1, D_2, \ldots, D_k$ and $D_o$ are domains of $I_1, I_2, \ldots, I_k$ and $O$ respectively. In a simple case where data are 32-bit integers, a domain $D_i$ already ranges up to $2^{32} - 1$. To count the number of possible outputs, one may be tempted to think of an exhaustive counting as follows:

$$N = 0$$

for all $v$ in $D_o$

    if (assert $O != v$ is violated) then
        $N \leftarrow N + 1$
    end if
end for

The assertion can be verified by formal methods such as model checking. Assuming we have a very powerful model checking tool that can verify each assertion in one second, the procedure would take around $2^{32}$ seconds, which is approximately 136 years. In fact, it is easy to prove by Rice’s theorem [4] that the problem of counting possible values of a program output is undecidable.

The first automated method that could precisely quantify information leaks was proposed by Backes et al. [5]. The method can be divided into two stages: first, it employs model checking to compute an equivalent relation $R$ on the set of confidential inputs w.r.t. observable outputs; secondly, if this relation $R$ can be represented by a system of linear integer inequalities $Ax \geq b$, which means it is a bounded integer polytopes, then a variant of Barvinok’s algorithm [6] can be used to count the number of integer solutions of $R$. While this is an important work as the first effort on automation of QIF analysis, there is little hope that real-world programs will satisfy this condition.

Meng et al. introduce an approximate method, which we call BitPattern, to calculate an upper bound on the number of possible outputs in [12]. The key idea is as follows: if all possible values of the output $O$ are very close to each other in the state space, then the bit vectors representing them have a lot of similarities, called bit patterns. The authors discover these patterns as a SAT formula, then employing Mathematica [4], a heavyweight commercial #SAT solver, to count the number of solutions, which is an upper bound on the number of possible outputs. The authors restrict themselves to C-like programs without loops, and leave automation of the method for future work.

Contribution. In summary, our contributions in this paper are as follows:

1. We propose a novel method for precise QIF analysis.
2. We analyse the BitPattern method, redesign it to make it fully automated and able to handle Java programs.
3. We implement the two methods in an open-source prototyping tool: jpf-qif, the first one to support information-theoretic QIF analysis.

3. METHODOLOGY

This section describes our method which we call Symbolic Quantitative Information Flow (SQIF).

3.1 A symbolic representation

The key idea behind SQIF is that instead of checking every concrete value one by one, we build a procedure to process multiple values at a time. To do this, we need a representation that can denote a set of values. The way a computer stores data in vectors of bits suggests a symbolic representation that we define as follows: we consider a set of boolean variables $\Phi := \{p_1, p_2, \ldots, p_K\}$, representing a variable of $K$ bits in the computer memory. In order to count the models representing possible outputs of program $P$, we need a formula $\Gamma$ such that each model of $\Gamma$ corresponds to a concrete value of the output $O$. We also need a decision procedure isSAT to check the satisfiability of $\Gamma$.

For a program $P$ with an output $O$ of data type of size $K$, $O$ is stored in the computer memory as a bit vector $bv_o$ of $K$ bits: $bv_o = b_{K-1} \cdots b_1$. We set up $\Gamma$ as a bijective mapping $\Gamma' : bv_o \rightarrow \Phi$, which can be implemented by adding the code in Figure 1 to the original program. The symbolic

$$\text{for all element } b_i \text{ in vector } bv_o \text{ do}$$

if ($b_i == 1$) then
    $p_i = \text{True}$
else
    $p_i = \text{False}$
end if
end for

Figure 1: Symbolic representation conversion

formula $p_i$ is a shorthand notation for the family of sets $\{\Phi := \{p_1, p_2, \ldots, p_K\} : p_i = \text{True}\}$. This family of sets can represent up to $2^{K-1}$ concrete values. Similarly, $p_1 \land \neg p_2$ represents a family of sets representing up to $2^{K-2}$ concrete values. 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 $\Phi$.
3.2 A symbolic QIF framework

The exhaustive counting procedure discussed in the previous section is inefficient, but intuitive: the only solution for precise counting is searching for all possible solutions. The source of inefficiency is that the procedure checks all concrete values of the data type, while the domain of the output $O$ is often small (note that we aim to tolerate small leaks, not to quantify the big ones). The symbolic QIF framework we propose here systematically explores the symbolic representation $\Phi$ of the output, and trims infeasible values in the process. For example, if we discover that $p_1$ is a tautology, then we can trim $2^{31}$ concrete values represented by $\neg p_1$, thus approximately saving 68 years compared with the exhaustive counting.

A high level framework to explore the state-space and quantify the leaks of confidential data is described in Figure 2. The recursive call $\text{SymCount}$ is described in Figure 3. $\Phi$, $\Psi$ and $N$ are passed by reference, while $pc$ and $i$ are passed by value. $\Phi$ is the symbolic representation described in the previous section, and $\Psi$ keeps the models of $I$ being explored. $N$ is the cardinality of $\Psi$, and the procedure SymbolicQIF returns $\log_2(N)$ as the maximum leakage of confidential data. $K$ is the size of the data type, e.g. $K = 32$ if $O$ is a 32-bit integer, and $i$ is the depth of the recursive call. In the process of exploring the state-space, the explored predicates are kept in a trace, which we name $pc$ in referring to path condition in symbolic execution, discussed further in the next section; $pc$ is incrementally updated when the search progresses.

At the heart of any QIF method is always a counting technique, and ours is described in the method $\text{SymCount}$ in Figure 3. To illustrate the technique, we consider a case study of data sanitization from [12], which is shown in Figure 4. All the data are 32-bit integers, the confidential data

\begin{verbatim}
function SymbolicQIF(\Phi)
  \Psi = \epsilon, N = 0, i = 1
  pc ← InitializePC()
  SymCount(\Phi, \Psi, N, pc, i)
  return \Psi, log_2(N)
end function
\end{verbatim}

Figure 2: Symbolic QIF analysis

\begin{verbatim}
1: function SymCount(\Phi, \Psi, N, pc, i)
2:  pc1 ← pc ∧ p_1
3:  if (isSAT(pc1)) then
4:    if (i == K) then
5:      \Psi ← \Psi ∪ {pc1}
6:      N ← N + 1
7:    else
8:      \text{SymCount}(\Phi, \Psi, N, pc1, i + 1)
9:    end if
10:  end if
11:  pc2 ← pc ∧ \neg p_1
12:  if (isSAT(pc2)) then
13:    if (i == K) then
14:      \Psi ← \Psi ∪ {pc2}
15:      N ← N + 1
16:    else
17:      \text{SymCount}(\Phi, \Psi, N, pc2, i + 1)
18:    end if
19:  end if
20: end function
\end{verbatim}

Figure 3: Symbolic counting for QIF

$H$ is only manipulated if it is in an acceptable range, namely from 0 to 15. However, while manipulating $H$, the program leaks information in the process. It is trivial to prove that only integer values from 8 to 23 are possible outputs of this program, i.e. the number of possible outputs $N = 16$.

At the beginning, all variables are initialised as in Figure 2: the method InitializePC sets $pc$ as empty. The method SymCount is then called to count the number of possible models of $I$. When a variable $p_i$ is in consideration, we systematically explore in the same way for both $p_i$ and $\neg p_i$. Hence, the block of code from line 3 to line 11 and the one from line 12 to line 20 in Figure 4 are symmetric; we only explain the first one.

A trace of the method is described in Figure 4. At the first call of $\text{SymCount}$: $i = 1$, the variable $p_1$ is in consideration, SQIF takes one step forward by adding $p_1$ to the trace like in line 3. Since $pc$ is initialised to be empty, $pc_1 = p_1$. The method $\text{isSAT}$ is called to check whether $I \vDash \Psi$ holds, which can be done by using assertion to check the validity of $\neg p_1$ in a Java program as follows:

\begin{verbatim}
assert \neg p_1;
\end{verbatim}

A model checking tool like Java Pathfinder (JPF) [1] can be used to verify this assertion, $\text{isSAT}$ will return $True$ if the assertion fails, and $False$ otherwise. In this example, $\text{isSAT}$ would return $True$ since all odd values from 9 to 23 are possible outputs satisfying the condition $p_1$. Therefore, SQIF proceeds by calling $\text{SymCount}$ with $i = 2$. Similarly,
In this way, we can construct the bit vector $O$ variable $i$. We choose to apply our method to programs developed in $O$ for the output we have already explained. In the previous section, we explained that each program always terminates and has no recursion, loops can be treated as a bounded model of runtime behaviour, which means programs are complete. In order to use SE as a verifying technique, we assume SE as a hybrid of verifying and testing. Symbolic execution (SE) is a hybrid of verifying and testing. Figure 4, BitPattern discovers that the assertion above is valid for $6 \leq i \leq 32$. For $1 \leq i \leq 5$, neither $b_i = 0$ nor $b_i = 1$ are valid. Thus, the bit vectors representing possible outputs of $O$ have the same pattern: $00...0$. The whole process is performed manually by the authors. Bit patterns are discovered by making queries about the bits of the output $O$: for example the following STP query tests whether bit $i$ of $O$ is necessarily 0.

\[
\text{QUERY}(O[i] : i = 0)\]

We redesign the BitPattern method, and make it fully automated and able to handle Java programs: we extract bits from the output as in (2), then replace the queries about the bits of the output $O$ with the condition $H < 16$. For $1 \leq i \leq 5$, neither $b_i = 0$ nor $b_i = 1$ are valid. Thus, the bit vectors representing possible outputs of $O$ have the same pattern: $00...0$. The whole process is performed manually by the authors. Bit patterns are discovered by making queries about the bits of the output $O$: for example the following STP query tests whether bit $i$ of $O$ is necessarily 0.

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\[
\text{QUERY}(O[i] : i = 0)\]
In general, we transform bit patterns into CNF formula in DIMACS format, then use ReLSat [2], a lightweight open-source #SAT solver, to perform model counting.

Both SQIF-SE and BitPattern are implemented in an open-source prototyping tool, jpf-qif [1], as an extension of JPF.

5. PRELIMINARY EXPERIMENTS

In the illustrative example in Figure 5, there is a direct flow from the confidential data $H$ to the output $O$ via assignment. Consider another example in which the program indirectly copies $H$ to $O$ if $H \leq 6$ as follows:

```plaintext
0 = 0;
if (H == 0) O = 0;
else if (H == 1) O = 1;
else if (H == 2) O = 2;
else if (H == 3) O = 3;
else if (H == 4) O = 4;
else if (H == 5) O = 5;
else if (H == 6) O = 6;
else O = 0;
```

Meng et al. reported an elapsed time of 45 ms, and BitPattern returns a bound of 3 bits. With the same example, it takes SQIF-SE 717 ms to count 7 possible outputs, and concludes a bound of 2.81 bits.

In previous case studies, BitPattern performs quite accurately when possible outputs are in the same range, e.g. 8..23 and 0..6. Consider a similar case study of a family of programs that each have exactly 10 feasible outputs:

```plaintext
if (H == r1) O = r1;
else if (H == r2) O = r2;
... 
else if (H == r9) O = r9;
else O = r10;
```

When $r1$ to $r9$ are generated uniformly and independently, the possible outputs diverge in the state space. BitPattern greatly overestimates the bound on information leakage. With 20 such programs, Meng et al. reported an average result of a bound of 18.645 bits in 5 seconds. On the other hand, SQIF-SE always finds exactly 10 outputs in around 1 second, which results in a bound of 3.322 bits.

6. CONCLUSION

In this paper we propose SQIF, a novel method to mitigate the state-space problem in QIF analysis. We have built jpf-qif, the first tool to support information theoretic QIF analysis. Compared with the precise QIF analysis in [3], SQIF can handle non-linear relations of various data types. Compared with BitPattern, SQIF is always more precise, but it is slower when leaks are in the same range. In contrast, SQIF is better in both effectiveness and efficiency when leaks diverge in the state space. An immediate direction for investigation is to combine SQIF with a cheap qualitative method, e.g. type system, to decide quickly if the program satisfies non-interference. This will improve the efficiency of the tool when programs are strictly secure.

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7. REFERENCES


