Dynamic Policies Revisited

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**Abstract**—Information flow control and dynamic policies is a difficult relationship yet to be fully understood. While dynamic policies are a natural choice in many real-world applications that downgrade and upgrade the sensitivity of information, understanding the meaning of security in this setting is challenging. In this paper we revisit the knowledge-based security conditions to reinstate a simple and intuitive security condition for dynamic policies: A program is secure if at any point during the execution the attacker’s knowledge is in accordance with the active security policy at that execution point. Our key observation is the new notion of policy consistency to prevent policy changes whenever an attacker is already in possession of the information that the new policy intends to protect. We use this notion to study a range of realistic attackers including the perfect recall attacker, bounded attackers, and forgetful attackers, and their relationship. Importantly, our new security condition provides a clean connection between the dynamic policy and the underlying attacker model independently of the specific use case. We illustrate this by considering the different facets of dynamic policies in our framework.

On the verification side, we design and implement DynCoVer, a tool for checking dynamic information-flow policies for Java programs via symbolic execution and SMT solving. Our verification operates by first extracting a graph of program dependencies and then visiting the graph to check dynamic policies for a range of attackers. We evaluate the effectiveness and efficiency of DynCoVer on a benchmark of use cases from the literature and designed by ourselves, as well as the case study of a social network. The results show that DynCoVer can analyze small but intricate programs indicating that it can help verify security-critical parts of Java applications. We release DynCoVer publicly to support open science and encourage researchers to explore the topic further.

**1. Introduction**

Information flow control provides an appealing security framework for reasoning about dependencies between information sources and information sinks, and for ensuring that these dependencies adhere to desirable security policies. In a language-based setting, this security framework has the following ingredients: (1) an execution model which is given by the execution semantics of a program; (2) an attacker model specifying the observation power of an attacker over the attacker-visible sources and sinks; (3) a security policy specifying, for each execution point, the permitted information flows from sources to sinks, disallowing information flows from secret/high sources to public/low sinks; (4) a security condition (or security property) capturing a program’s security with respect to an execution model, an attacker model, and a security policy. A classical security condition is noninterference requiring that any two executions starting with equal values on public sources yield equal values on public sinks [1].

A common trait in much recent work on information flow control has been the appeal to attacker-centric security conditions based on the concept of knowledge as a fundamental mechanism to bring out what security property is being sought and compare it with the knowledge permitted by the security policy [2], [3], [4]. Arguably, this appeal to knowledge, usually as equivalence relations on initial states, has produced clear and intuitive security conditions able to accommodate various notions of information downgrading (declassification) on which soundness arguments for enforcement mechanisms, e.g., security type systems, can be based [5], [6], [7]. In a nutshell, knowledge-based security conditions capture an intuitive requirement: A program is secure with respect to a security policy if at any point during the program’s execution, the attacker’s knowledge is not greater than the knowledge permitted by the active security policy at that execution point.

While this simple and elegant condition is well-understood for static multilevel security policies that only downgrade the sensitivity of information, it does not appropriately capture the security requirements of systems that change their security policies dynamically, thus both downgrading and upgrading the sensitivity of information in response to security-sensitive events. This is not satisfactory because dynamic policies are a natural choice for many real-world applications, e.g., healthcare systems, social networks, database systems, where access to information may be granted or revoked to different principals in accordance with their specific role at a given moment [8], [9], [10], [11]. Existing works address the challenge of dynamic policies by proposing security conditions that capture specific facets of a targeted use case [12], [13], [2], [14], [15], [16], [8], [9]. Broberg et al. [11] systematize existing research on dynamic policies illuminating the different facets exhibited by existing security conditions.

In this paper we revisit the state-of-the-art of security conditions for dynamic policies to reinstate attacker-centric knowledge-based conditions. Our starting point is the work of Askarov and Chong [8] which proposes a general framework for weakening of the attackers’ observation power to accommodate dynamic policies. We further revise and develop this framework targeting three types of realistic attackers: (1) perfect recall attackers recalling all observations on public sinks; (2) bounded memory attackers recalling a bounded number of observations on public
Our key observation is the notion of policy consistency to reflect the observation power of an attacker and thus prevent a policy change whenever the attacker is already in possession of the information that the new policy intends to protect. For example, under the model of a perfect recall attacker, a policy change that revokes access to a resource that the attacker has already observed (possibly at a past time when access to that resource was granted to the attacker) should result in an inconsistent policy, since it violates the assumption on the perfect recall attacker. Unfortunately, existing works assume that policy changes are always consistent, which has often resulted in ad hoc and unintuitive security conditions. This simple but fundamental insight allows us to reestablish clear and intuitive attacker-centric knowledge-based conditions for dynamic policies. More importantly, the new security conditions are in line with the above-mentioned ingredients required by a security framework and they provide a clean separation between policy concerns and enforcement concerns. A policy designer can instantiate our framework in accordance with the security requirements for the use case at hand, by specifying the most suitable attacker model. We validate our framework by revisiting the facets of dynamic policies by Broberg et al. [11]. Moreover, in contrast to Askarov and Chong [8], we prove that, in absence of inconsistent policy changes, a perfect recall attacker is indeed stronger than a bounded memory attacker and a forgetful attacker. Finally, we discuss policy updates whenever inconsistencies are detected.

Our second contribution is the design and implementation of algorithms for verifying dynamic information-flow policies via symbolic execution and SMT solving. Our verification method operates by first extracting program dependencies and then using these dependencies to check dynamic policies for a range of attackers including perfect recall, remembering any information they observe during a program’s execution. A popular security condition [3], requiring that at any location i the attacker’s knowledge $p_i$ is smaller than the policy knowledge (i.e., the knowledge allowed by the security policy) $k_i$.

$$p_i \subseteq k_i$$

Consider the scenario in Program 1 where user Alice purchases a time-limited subscription on a streaming service to watch a movie. After the subscription ends, the security policy changes, however Alice still attempts to watch the movie.

One could argue that this program should be considered insecure because Alice watches the movie when she no longer has a subscription. Here, the release of knowledge is considered transient and it should satisfy the active security policy at every program location. Hence, despite being perfect recall, Alice should not be able to watch the movie at a time this is disallowed by the policy (line 4). In fact, equation (1) holds in line 2 since Alice watches the movie and the policy allows her to watch the movie, i.e., hence $p_2 \subseteq k_2$ since $\{\text{movie}\} \subseteq \{\text{movie}\}$. However, in line 4 we have that $p_4 \not\subseteq k_4$ since $\{\text{movie}\} \not\subseteq \{\text{movie}\}$, where $\{\text{movie}\}$ denotes the set of all possible movies. Hence, the program is correctly rejected by the security condition (1).

In summary the paper offers these contributions:

- We revisit the state-of-the-art security conditions for dynamic policies and reinstate clear and intuitive knowledge-based conditions based on the observation power of the attacker (Section 2 and 4).
- We show how our new framework can be used to capture the different facets of dynamic policies proposed in the literature (Section 5).
- We design verification algorithms based on symbolic execution and SMT solving to check the security of Java programs for a range of attacker models, as well as to detect inconsistent policies (Section 6).
- We implement DYNCOVER [20] and evaluate the efficiency and effectiveness on a collection of benchmarks and the case study of a social network (Section 7).

2. Problem Setting and Solution Overview

This section gives an informal overview of dynamic policies discussing the challenges, pointing out limitations of existing solutions, and arguing for revised knowledge-based security conditions. The key question is: What is a suitable security condition for dynamic policies?

To provide a common ground for comparing the different approaches, we borrow the notation and examples from Askarov and Chong [8] and Broberg et al. [11]. We write $A \rightarrow B$ ($A \not\rightarrow B$) to denote a security policy allowing (disallowing) information flows from security level $A$ to security level $B$. We assume that no information flows between different security levels are allowed initially. For simplicity, the name of a program variable (e.g., $\text{movie}$) will match the security level of the variable (e.g., $\text{Movie}$).

We write $k_i$ and $p_i$ to denote the attacker’s knowledge and the active security policy at program location $i$, respectively. By default, we assume that attackers are perfect recall, remembering any information they observe during a program’s execution. A popular security condition [3], [4], [10], which is used in systems that handle only declassification of information, is given by equation (1) requiring that at any location $i$ the attacker’s knowledge $k_i$ is smaller than the policy knowledge (i.e., the knowledge allowed by the security policy) $p_i$.

1In this notation, knowledge corresponds to uncertainty, hence the bigger the set, the smaller the knowledge (see Section 4).
Consider now Program 2, a variation of Program 1, displaying the message NoSubscription! after the second policy change. This program is also rejected by condition (1) since $p_4 \not\subseteq k_4$, i.e., $All \not\subseteq \{\text{movie}\}$, even though the NoSubscription! message does not leak anything.

To address this case, Askarov and Chong [8] identify the power of perfect recall attacker as a key issue and present a security condition that accounts for weaker attackers. Their security condition requires that the attacker’s change in knowledge should be allowed by the active policy, thus at any program location $i + 1$ the attacker’s knowledge $k_{i+1}$ should be smaller than the attacker’s prior knowledge and the policy knowledge at location $i$:

$$p_i \cap k_i \subseteq k_{i+1} \quad (2)$$

Condition (2) now accepts Program 2 as secure since $p_4 \cap k_3 \subseteq k_4$, i.e., $All \cap \{\text{movie}\} \subseteq \{\text{movie}\}$. However, surprisingly condition (2) also accepts Program 1 since $p_4 \cap k_3 \subseteq k_4$, i.e., $All \cap \{\text{movie}\} \subseteq \{\text{movie}\}$.

The root of the issue here is that perfect recall attacker is too powerful and can remember any observations made in the past, e.g., in line 2. To overcome this issue, Askarov and Chong only consider condition (2) for weaker attackers with bounded memory. For example, a bounded memory attacker that remembers only the last observation would similarly for a bounded memory attacker.

A key question arises at this point: How does a policy designer choose the right attacker model, and hence security condition, for their setting? While in principle there may always exist a bounded memory attacker that accommodates specific use cases as above, it is unclear what such attacker model should be. Askarov and Chong answer this question by requiring that condition (2) holds for all attackers, including perfect recall and bounded memory attackers. This is important because it enables compositional reasoning and facilitates enforcement by a security type system, however, security for all attackers can be too restrictive in settings where, e.g., only the perfect recall or a bounded memory attacker is realistic. In fact, Broberg et al. [11] discuss use cases where the same program can be considered either secure or insecure under different attacker models.

More importantly, condition (2) permits any policy changes although these changes may contradict the assumptions about the attacker. Consider Program 3 handling information about users’ salaries. Initially, both Alice and Bob allow Eve to learn their salaries, however, the program displays only the average salary to Eve. Then Alice decides that her salary should no longer be visible to Eve and the program displays Bob’s salary.

Let $As$ and $Bs$ be the salary of Alice and Bob, respectively. Under a perfect recall attacker, Program 3 satisfies condition (2). Indeed Eve can combine the average salary (line 2) and Bob’s salary to learn Alice’s salary, hence $k_5 = \{(As, Bs)\}$. Therefore, $p_4 \cap k_4 \subseteq k_5$ since $\{(All \times Bs) \cap \{(a, b)\} | (a + b) / 2 = (As + Bs)/2\} = \{(As, Bs)\} \subseteq \{(As, Bs)\}$. The program is also accepted for a bounded memory attacker that remembers only the last output.

Under the perfect recall attacker, we argue that Program 3 should not be accepted. The mere definition of perfect recall assumes that the attacker remembers any observations and can use these observations to infer information about the salaries of Alice and Bob. The real problem lies in the change of the policy in line 4. Because Eve’s knowledge in line 3 reveals some information about Alice’s salary (and Eve has perfect recall) the policy change in line 4 is inconsistent, trying to revoke access to a resource, i.e., Alice’s salary, that Eve has already some information about. Hence, the policy change in line 4 should be disallowed in the case of a perfect recall attacker. A similar argument applies to Program 1 and Program 2 under the perfect recall attacker. The reader may find this surprising, especially for Program 2, but, again, the attacker has perfect recall, hence they remember the observation of movie in line 2. Therefore, restricting access to the attacker to some information they already have is meaningless and should be prevented by the security condition. In fact, by considering the intersection of the knowledge and policy $(p_i \cap k_i)$, condition (2) effectively enforces condition (1) under a different policy $p = p_i \cap k_i$. This leads us to proposing a new (class of) conditions which is parameterized by an attacker $A$:

$$p^A_i \subseteq k^A_i \quad (3)$$

In contrast to condition 1, condition 3 makes the role of the attacker explicit in the definitions of knowledge and policy, as well as considers the consistency of a security policy. We instantiate the security condition (3) to characterize three attacker models: perfect recall, bounded memory, and forgetful. For the perfect recall attacker, our security condition corresponds to equation (1), ensuring that policy changes are consistent at any program location $i$. For a bounded memory attacker, the condition captures a weaker attacker which remembers observations up to a predefined bound $m$, extending the weaker attackers of Askarov and Chong [8] with policy consistency checks. Finally, the forgetful attacker captures scenarios in which the release of knowledge is transient and limited to the event of a policy change, thus ensuring that the attacker forgets (or resets) their knowledge whenever there is a
policy change. This attacker model allows: (1) Reject Program 1 since Alice attempts to (re-)watch the movies at a time this is prevented by the active policy; (2) Accept Program 2 (Program 3) since Alice (Eve) does not learn any information about movie (Alice’s salary) at any time this is prevented by the active policy.

3. Language Design

We present a simple imperative language with extended commands for policy change and outputs. We assume that outputs are performed on channels associated with security labels \( X, Y, \ell \in \mathcal{L} \).

**Syntax** Figure 1 presents the syntax of our language. Expression \( e \) consists of program variables \( x, v \), values \( v \), and binary operations \( \otimes \). For simplicity, we restrict values to only integers \( n \). Most of the commands are standard with the exception of output and setPolicy. Output command \( \text{output}_c(e) \) evaluates expression \( e \) to some value \( v \) and then outputs \( v \) on channel \( \ell \). Command \( \text{setPolicy}(p) \) sets the current security policy to \( p \).

**Semantics** Figure 2 presents the operational semantics of the language. A configuration is a tuple (i.e., set of Policy) \( \langle c, \sigma, p \rangle \) of the underlying system itself, e.g., restricting access to a service, and these operations are typically carried out by the system administrator. This assumption applies to real-world scenarios where a user does not directly control their access rights, while the policies governing these access rights are introduced to the system by an administrator. Nevertheless, our framework can be easily extended to accommodate observable policy changes by considering such events similar to program outputs.

4. Security Framework

In this section, we present knowledge-based and attacker-centric security conditions for a range of relevant attackers and explore their differences. As discussed informally in Section 2, the security condition has the form \( p^\alpha_i \subseteq k^\alpha_i \), meaning that in every step of the program’s execution, the active security policy should be the upper bound of the attacker’s knowledge. We instantiate this condition for different attacker models to consider security-relevant events such as policy changes and attacker-visible program outputs.

4.1. Security Polices

We consider a multi-user setting where a program controls a server on behalf of different users which are identified by security labels \( \ell \in \mathcal{L} \). For simplicity, we assume that the users’ data is read upfront and resides in the initial store of the computation. Section 4.4 presents an extension to programs with arbitrary inputs.

A security policy \( p \) is a list of flows of the form \( \ell_1 \rightarrow \ell_2 \) and is used to define what an observer at a specific security label \( \ell_2 \) is allowed to learn about the initial values with label \( \ell_1 \). We assign security labels to the variables and use function \( \Gamma \) which is a mapping from variables to security labels (i.e., \( \forall v \in \text{Vars}, \ell \in \mathcal{L} \). We discuss fine-grained policies in programs with arbitrary inputs. Throughout this paper, we use \( p_{\text{init}} \) as a predefined initial policy from which all programs start their execution. It is a simple reflexive policy that only allows a security label to flow to a corresponding channel with the same label (i.e., \( X \rightarrow X \)). We use \( X \rightarrow A \) to add new non-reflexive flows to the list of allowed policies, and \( X \not\rightarrow A \) to revert (disallow) such a flow.

A security policy induces an equivalence relation over stores. Intuitively, for the flow \( X \rightarrow A \), two stores are related to each other by an equivalence relation for an observer on channel \( A \) if they have identical values for variables with security label \( X \). Formally:

\[
\sigma \equiv_A^p \sigma' \iff \forall x \in \text{Vars} : \Gamma(x) = X \land X \rightarrow A \in p.
\]

We write \( [\sigma]^p_A \) for the set of stores in the same equivalence class as \( \sigma \) with respect to a policy \( p \) and an observer \( A \). If \( \sigma \equiv_A \sigma' \) (i.e., \( \sigma' \in [\sigma]^p_A \)), then an observer on channel \( A \) cannot distinguish between stores \( \sigma \) and \( \sigma' \). Henceforth, we call such an observer the attacker and fix its label to \( A \). Observe that more fine-grained policies can be defined in the expected manner by refining the definition of \( [\sigma]^p_A \), e.g., by mapping each label to an equivalence relation on program stores as defined by the policy \( p \) [10], [21]. We discuss fine-grained policies in Section 6.

In line with existing work on dynamic policies [8], [10], [21], we assume that policy changes are not observable externally, e.g., to an attacker \( A \). In our multi-user setting, policy changes result from internal events of the underlying system itself, e.g., restricting access to a service, and these operations are typically carried out by the system administrator. This assumption applies to real-world scenarios where a user does not directly control their access rights, while the policies governing these access rights are introduced to the system by the administrator. Nevertheless, our framework can be easily extended to accommodate observable policy changes by considering such events similar to program outputs.
Values

Expressions e ::= v | x | e₁ ⊕ e₂
Commands c ::= skip | x := e | c₁; c₂ | if e then c₁ else c₂ | while e do c | output_e(e) | setPolicy(p)

Figure 1: Language Syntax

Program 4

1 setPolicy(X \rightarrow A);
2 output_A(1);
3 setPolicy(X \not\rightarrow A);
4 setPolicy(x);

4.2. Security Conditions and Attacker Models

Our main focus is on the confidentiality of data, hence we consider a (logically omniscient) passive attacker that knows the program’s source code and wants to deduce sensitive information about the initial store values. Our goal is to identify security conditions for dynamic policies by investigating the relationship between the attacker’s knowledge and the policy knowledge for a range of attackers.

We present our knowledge-based security conditions for perfect recall and forgetful attackers. For space reasons, we refer the reader to Appendix D for similar results on bounded memory attackers.

4.2.1. Perfect Recall Attacker. We model this attacker’s knowledge of the initial store \( \sigma \) as a set \( k \), which includes all of the possible stores that can produce the same observable trace. We assume the attacker with security level \( A \) is passively observing all outputs on channel with label \( A \). When a command such as output_\( A \)(v) executes, the attacker sees this output and learns the value v. We define attacker’s knowledge as:

**Definition 1 (Perfect Recall Attacker Knowledge at Point i).** Given program \( c \) with initial store \( \sigma \), and initial policy \( p_\text{init} \), which produces trace \( t \) after \( i \) execution steps, i.e., \( \langle c, \sigma, p_\text{init} \rangle \xrightarrow{ i } t \), the knowledge of a perfect recall attacker that observes program outputs on channel \( A \) is defined as:

\[
 k_i(c, \sigma, p_\text{init}, A) = \{ \sigma' \mid \langle c, \sigma', p_\text{init} \rangle \xrightarrow{ i }_{t} A \land t|_{A} = t'|_{A} \}
\]

Intuitively, \( k_i(c, \sigma, p_\text{init}, A) \) is the set of initial stores that the attacker at channel \( A \) believes are possible when observing the trace \( t|_{A} \) at execution point \( i \). Thus, the larger the knowledge set, the less certain the attacker is of the actual values in \( \sigma \).

The Perfect Recall attacker has unlimited memory and can remember all outputs on channel \( A \). This attacker is the most powerful attacker, because once they observe an output value they will never forget it, hence, a policy can no longer restrict the knowledge resulting from the attacker’s past observations. Arguably, in presence of such an attacker, programs like 3 should be rejected, because, as mentioned earlier, we cannot make the attacker forget what they already know. Therefore, it is not reasonable to issue a new policy that prevents this attacker from learning information which they already know.

With this intuition in mind, we need to ensure that any policy update is consistent with the current knowledge of the perfect recall attacker:

**Definition 2 (Policy Consistency).** For all execution points \( i \), and security policies \( p_i \) such that

\[
\langle c, \sigma, p_i \rangle \xrightarrow{ i }_{t} \{ \text{setPolicy}(p_i); c_i, \sigma_{i-1}, p_{i-1} \}
\]

we say policy \( p_i \) is consistent with the current attacker knowledge \( k_{i-1}(c, \sigma, p_{init}, A) \) if \( [\sigma]_{A}^{p_i} \subseteq k_{i-1}(c, \sigma, p_{init}, A) \).

A security policy induces an equivalence relation over all possible stores, and \( [\sigma]_{A}^{p_i} \) is a set of stores in the same equivalence class as initial store \( \sigma \). Since by Definition 1 attacker knowledge \( k_{i-1}(c, \sigma, p_{init}, A) \) is also a set of initial stores, it is straightforward to check \( [\sigma]_{A}^{p_i} \subseteq k_{i-1}(c, \sigma, p_{init}, A) \).

For example in Program 4, the new policy \( X \not\rightarrow A \) in line 3 is consistent, because the attacker does not learn anything about \( x \) by observing the output in line 2, hence the new policy that disallows learning \( x \) is consistent. However, under this new policy, Program 4 should be rejected, because the output of \( x \) in line 4 happens at a time when the policy does not allow it. We follow this intuition to define security.

**Definition 3 (Observation Security).** For all execution points \( i \) such that

\[
\langle c, \sigma, p_i \rangle \xrightarrow{ i }_{t} \{ \text{output}_A(x); c_i, \sigma_{i-1}, p_{i-1} \}
\]

program \( c \) is secure if \( [\sigma]_{A}^{p_i} \subseteq k_i(c, \sigma, p_{init}, A) \).

This definition ensures that, whenever an output on channel \( A \) happens, the attacker’s knowledge at that point is allowed by the current policy. In other words, the policy
places an upper bound on the attacker’s knowledge\(^2\), and if the knowledge does not exceed that limit, the program is secure.

**Definition 4 (Security Condition for Perfect Recall).** A program \(c\) is secure under the perfect recall attacker if Definitions 2 and 3 hold.

We deliberately separate Definitions 2 and 3 to distinguish between policy consistency checks and security checks. A failed policy consistency check means that there is a mismatch between the attacker’s power and the new policy. Therefore, a policy inconsistency can be repaired with a new policy that takes into account the attacker’s knowledge. On the other hand, a failure of observation security (Definition 3) cannot be repaired and it implies that the program is insecure.

### 4.2.2. Forgetful Attacker

We now consider an attacker that resets its knowledge after a policy change. This is especially useful for real-world applications where the release of information is not permanent and should be consistent with the active security policy at the time of the release. Program 1 in Section 2 is an example of the usefulness of this attacker model. Intuitively, a policy change at an execution point \(i\) means that, from the point \(i\) onward, the new policy should govern the release of information and any past knowledge should be ignored. The term “forgetful attacker” may not exactly reflect a real world attacker that suddenly forgets everything after a policy change. It is an artifact of modeling scenarios in which a policy change enforces a new condition on information release, independently of what an attacker may already know as result of past observations. For example, an employee may have accessed a company’s information (and even stored it externally), however, no access to the same information should be allowed when they leave the company. This setting requires ignoring the attacker’s knowledge prior to the policy change, essentially resulting in a forgetful attacker. We first discuss some examples illuminating the subtleties of forgetful attackers and then present our security condition.

Consider Program 5 as an example. When the execution reaches the `splitPolicy` command in line 5, there are two possible traces that the attacker could have observed: \(t_1 = y.1\) and \(t_2 = y\), both leaking the value of \(y\). One may think that trace \(t_1\) leaks the sign of \(y\) but this is not the case. Because the attacker’s knowledge is derived through observations and the policy changes are not observable, the attacker cannot tell which if statement has produced the output 1 of trace \(t_1\). Therefore, these traces reveal nothing about \(x\), and at the time of policy change, the attacker only knows \(y\) as stipulated by the policy in line 1. The new policy now prevents the attacker from learning \(y\) again, hence no outputs after the policy change should leak \(y\). In fact, all executions after the policy change will output the values 1 and 2. Note that even though the output 1 on line 7 happens after the policy change, it still cannot leak the sign of \(x\), therefore, Program 5 is secure.

Program 6 is similar except that it outputs the value of \(y\) at lines 4 and 7. In this case, if the execution did not take the first if statement, the attacker observes the trace \(t = 1\) which leaks nothing about \(x\) or \(y\), thus at the time of policy change the attacker forgets nothing. However, when \(y\) is outputted in line 7, the attacker learns this value and because this is not allowed by the policy, the program is insecure.

Programs can leak through the progress of computation e.g., when the number of outputs depends on information that is disallowed by the policy [22]. It is our intuition that forgetful attackers should not forget these progress leaks. Once the length of a trace, i.e., the number of outputs, leaks some information, any extension of that trace will leak the same information again, thus it is not reasonable for a forgetful attacker to forget progress leaks. This can be captured by making forgetful attackers remember the number of observed outputs, including the ones that happened before a policy change. This approach captures progress leaks even when they manifest after a policy change. This is similar to the idea of counting attackers presented in van Deft et al. [10].

Program 7 illustrates the effect of progress leaks on the attacker’s knowledge. When the execution reaches the policy change at line 7, the attacker could have observed trace \(t_1 = 1\) or \(t_2 = 1.1\). Since the policy change event is not observable by the attacker and any program execution can yield at least 2 outputs (e.g., trace 1.1), the attacker learns nothing about \(x\). Later, after the new policy at line 7 becomes active, the output at line 8 occurs. One of the traces that the attacker could have observed at this point is \(t_2 = 1.1.1\). This trace leaks that the first if statement must have been executed and \(x > 0\), which violates the active policy. Therefore, the number of outputs leaks the sign of \(x\), which happens after the policy change, hence the program should be flagged as insecure.

With these intuitions in mind, we proceed to define the knowledge of forgetful attacker. We call the trace between two policy changes an epoch and use the policy events (\(np(p)\)) to partition the trace into multiple epochs. At each step, the observable events of the last epoch, as well as the number of events in previous epochs can affect the forgetful attacker’s knowledge. To be able to separate the last epoch from the whole trace, we define the following auxiliary functions: `splitPolicy(t)` takes a trace \(t\) and returns a tuple containing all events before and after the last new policy (\(np(p)\)) event; \(split(t, n)\) takes a trace \(t\) and a number \(n\), and returns a tuple containing the first \(n\) events and the remainder of events in the trace.

**Definition 5.** Given a trace \(t\) such that \(t = \alpha_1...\alpha_i...\alpha_k\),

\[
\text{splitPolicy}(t) = \begin{cases} (c, t) & \text{if } \alpha_i \neq np(p) \ r = 1...k \\ (\alpha_1...\alpha_i , \alpha_i+1...\alpha_k) & \text{if } \alpha_i = np(p) \ \land \ \alpha_r \neq np(p) \ r = i + 1...k \\ (t, \epsilon) & \text{if } \alpha_k = np(p) \end{cases}
\]

**Definition 6.** Given a trace \(t\) such that \(t = \alpha_1...\alpha_i...\alpha_i+1...\alpha_k\),

\[
\text{split}(t, n) = \begin{cases} (t, \epsilon) & \text{if } k \leq n \\ (\alpha_1...\alpha_i , \alpha_i+1...\alpha_k) & \text{if } i = n \end{cases}
\]

Using these auxiliary functions, we can proceed to define the forgetful attacker’s knowledge as:
Definition 7 (Forgetful Attacker Knowledge at Point $i$).

Program $c$ with initial store $\sigma$ and initial policy $p_{\text{init}}$ produces trace $t$ after $i$ execution steps, i.e., $\langle c, \sigma, p_{\text{init}} \rangle \xrightarrow{i} t$.

Let $(t_1, t_2) = \text{splitPolicy}(t)$, we define for the knowledge of a forgetful attacker that observes the program outputs on channel $A$ as:

$$k^{\text{frg}}_i(c, \sigma, p_{\text{init}}, A) = \{ \sigma' | \langle c, \sigma', p_{\text{init}} \rangle \xrightarrow{i} t' \wedge (t'_1, t'_2) = \text{split}(t'|A|, t_1|A|) \wedge t'_2 = t_2|A\}$$

Intuitively, for each execution point $i$, we identify the traces before $(t_1)$ and after $(t_2)$ the last policy change. The goal is to forget the knowledge induced by attacker’s trace $t_1|A|$ and compute the knowledge induced by $t_2|A|$. We achieve this by considering any initial states that produce the same number of outputs as $t_1|A|$ and the same outputs as $t_2|A|$. Note that this condition (as all our conditions) is progress sensitive and accounts for progress leaks. We remark that progress leaks are never forgotten once they are revealed at some execution point.

We can now use the definition of knowledge from Definition 7 to obtain the security condition for forgetful attackers.

Definition 8 (Security condition for Forgetful Attacker).

For all execution points $i$ such that

$$\langle c, \sigma, p_{\text{init}} \rangle \xrightarrow{i} \langle \text{output}_A(c); c_i, \sigma_{i-1}, p_{i-1} \rangle \xrightarrow{i} \langle c_i, \sigma_i, p_i \rangle$$

program $c$ is secure if $[\sigma]^{p_i}_A \subseteq k^{\text{frg}}_i(c, \sigma, p_{\text{init}}, A)$.

Appendix B exercises the definition for Programs 5–7 to investigate their security.

We can now show that if a program is secure against the perfect recall attacker, it is also secure against less powerful attackers such as bounded memory attackers and forgetful attackers. Here, we present a theorem and prove this claim for the forgetful attackers.

Theorem 1. Given a program $c$, initial store $\sigma$, and initial policy $p_{\text{init}}$. If for all execution points $i$, $c$ is secure against perfect recall attacker $A_{\text{per}}$, it is also secure against forgetful attacker $A_{\text{frg}}$. Formally:

$$[\sigma]^{p_i}_A \subseteq k_i(c, \sigma, p_{\text{init}}, A_{\text{per}}) \quad\Rightarrow\quad [\sigma]^{p_i}_A \subseteq k^{\text{frg}}_i(c, \sigma, p_{\text{init}}, A_{\text{frg}})$$

Appendix D contains the proof of Theorem 1 and the corresponding theorem for bounded memory attackers.

4.3. Repairing Inconsistent Policies

An inconsistent policy means that the policy is incompatible with the current knowledge of the attacker. One approach is to always reject the programs with inconsistent policies, because $p_i \not\subseteq k_i$. Alternatively, we can suggest the user a new policy that is consistent with the attacker’s current knowledge. Generally, a policy change is inconsistent if it restricts access to information that has already been learned by the attacker. Our goal is to relax these restrictions and add what has been learned by the attacker to the new policy to achieve a consistent policy.

The intersection of the new policy and the attacker’s knowledge $(p_i \cap k_i)$ is a good candidate because it includes all of the new flows introduced by the new policy, and uses the knowledge of the attacker to relax the restrictions of the new policy. Intuitively, the consistent policy $p_i \cap k_i$ corresponds to the most adequate policy that meets the intention of the policy change $p_i$ while being in line with the attacker’s current knowledge $k_i$.

Definition 9 (Consistent Policy Repair). For all execution points $i$ such that

$$\langle c, \sigma, p_{\text{init}} \rangle \xrightarrow{i} \langle \text{setPolicy}(p); c_i, \sigma_{i-1}, p_{i-1} \rangle$$

the repaired policy $p'_i$ is induced by $[\sigma]^{p_i}_A \cap k_{i-1}(c, \sigma, p_{\text{init}}, A)$.

While previous approaches [8], [10], [21] use intersection as part of the security conditions, here we emphasize that it corresponds to a new consistent policy, thus making it explicit for the user that security of the program is checked against a different (repaired) policy.

4.4. Generalization to Programs with Inputs

In a framework of dynamic policies, it is natural to model new information arriving into the system via input channels. We show how our framework can accommodate programs with inputs with minimal changes. We extend the syntax of the language with an input command $\text{input}_x(\ell)$ which reads a value from the input channel with label $\ell$ and assigns it to variable $x$. Clark and Hunt [23] have shown that for deterministic interactive systems, streams are sufficient to model arbitrary interactive input strategies. An input stream is an infinite sequence of values representing the pending inputs on a channel. We assume there is one input channel for each security level $\ell$ and an input environment $\omega$ mapping labels to input streams. We extend the configurations $\langle c, \sigma, p, \omega \rangle$ with the
input environment $\omega$ and the evaluation steps as expected. We write $v : vs$ for a input stream with the first element $v$ and remaining elements $vs$, and $\omega[\ell \mapsto vs]$ for the input environment that maps input stream with label $\ell$ to $vs$ and otherwise behaves the same as $\omega$. The semantics of input command is defined as:

**Input**

$\omega(\ell) = v : vs \quad \omega' = \omega[\ell \mapsto vs]$

This command updates the store $\sigma$ with value $v$ for variable $x$, and continues with $vs$ as the remainder of the input stream of label $\ell$, while emitting the input event $i(v, \ell)$. Events and traces are extended with input events in the expected manner.

We can now define security policies as equivalence relations over input environments. Two input environments are equivalent for a policy $p$ and an attacker on channel $A$, i.e., $\omega \equiv_p^A \omega'$ iff $\forall \ell \rightarrow A \in p, \omega(\ell) = \omega'(\ell)$. We write $[\omega]^p_A$ for the equivalence class of $\omega$ with respect to the policy $p$ and attacker $A$. With these definitions at hand, we can easily redefine the attacker knowledge over input environments and use the same security conditions adapted with the new definitions of attacker knowledge and security policies. This extension are straightforward and we omit them here in the interest of space.

5. Facets of Dynamic Policies

In this section we revisit the facets of dynamic policies, introduced by Broberg et al. [11], and discuss them in our framework from an attacker-centric perspective. Our goal is to show how these facets can be accommodated in our framework, illuminating on the different types of flows. We have modified and adapted the use cases to fit our language model with explicit outputs.

**Time-transitive flows** A flow is time-transitive if it moves information from level $X$ to level $Z$ via a third level $Y$, while a direct flow from $X$ to $Z$ is never allowed by the policy. Program 8 illustrates such a flow. It reveals information about Patient to DrPhil who joined the hospital after Patient had left.

According to Broberg et al. [11] time-transitive flows should be considered insecure in scenarios where a data flow such as Patient $\rightarrow$ Hospital is only allowed temporary for as long as Patient is under treatment in the hospital. Our framework can identify the insecurity of such scenarios; when output$_{DrPhil}(\text{drPhil})$ happens it indirectly reveals the value of patientData which is not allowed by the active policy. A similar argument applies to bounded memory and forgetful attackers. The main reason for rejecting these flows is that the observer $\text{DrPhil}$ did not see the data at the time he was allowed to and the actual flow has happened at a time when patient had already left the hospital.

Broberg et al. [11] also interpret time-transitive flows as secure by considering the assignment in line 2 as a permanent declassification. Using permanent declassification means changing the label of patientData to Hospital permanently, however, this means that the policy Patient $\not\rightarrow$ Hospital becomes irrelevant, since patientData no longer has the label of Patient and hence it not affected by its policy. In our framework, this interpretation amounts to a program that allows flows from Hospital to DrPhil and subsequently outputs the data to DrPhil.

**Replaying flows** model scenarios in which when a piece of information is released, it can be released again, regardless of the active policy. Program 9 illustrates such a flow. When creditcard is written to a log file, it should be available until the log is cleared.

Replaying flows should be considered secure when the release of information is permanent [11]. Permanent release of information means that an observer can access any information they had learned before, irregardless of the active policy. For example in Program 9, if the output in line 2 permanently releases the creditcard information to Log, the observer at level Log can always access it later. This definition can be captured by our framework, by adapting the Definition 9 for inconsistent policies. This means that the new policy will be the intersection of the knowledge of the attacker $k$ and new the policy $p$, and since the output in line 2 adds creditcard to the knowledge of the attacker, $k \cap p$ will always include that knowledge, hence permanently releasing it.

However, considering information as permanently released is not always the natural choice in every situation; for example in Program 1, Alice should not have access to the movie after her subscription ended. Forgetful attackers in our framework are good candidates for dealing with such scenarios where we want to ignore the effects of the earlier release and accept or reject programs only based on the current active policy. This intuition is similar to the insecure time-limited subscription example of Broberg et al. [11].

**Direct Release** means that information is considered released as soon as the current policy permits the flow. Program 10 illustrates such a flow where salary is not printed to the screen when the flow is allowed, but it is printed when the flow is no longer permitted.

Broberg et al. [11] argue that these flows are insecure when the attacker can only observe information that is actively provided (through for example an output channel). In Program 10 nothing about salary has been printed to the screen, hence it makes sense to assume that an observer does not know this information. Our framework follows this intuition and rejects this flow under all attacker types and policy checks; because an attacker learns nothing from output of line 2 and the output on line 4 always violates the active policy.

However, this type of flow can be considered secure if we model attackers as constantly observing, directly in the memory, all the information which they are allowed to learn. We can model such a behavior by outputting all the variables with label Salary as soon as the policy Salary $\rightarrow$ Screen is activated. However, doing so effectively changes the nature of this flow to a replaying flow, and as it was discussed earlier, replaying flows can be secure only if we consider permanent release of information.

**Whitelisting flows** A flow is allowed whenever there is some part of the policy that allows for it. Program 3 in Section 2 is an example of whitelisting flows, where the observer Eve can use her knowledge of (Alice.salary + Bob.salary) / 2 and Bob.salary to learn the salary of Alice. For perfect recall attackers,
our framework rejects this class of programs because they have inconsistent policy changes. This is inline with the insecure example presented by Broberg et al. [11] which argue that information belonging to two entities Alice and Bob (in this case the average of their salaries) should be available only when both of them allow it.

Broberg et al. [11] presents Program 11 as a secure example for whitelisting flows, where first the encrypted value (secret XOR key) is released and then later the key. Broberg et al. [11] argue for the security of this example on the grounds that key is an encryption key, and “with the release of this key an observer learns the secret information that was earlier released under that key, even though part of the policy does not allow the secret to be released”. This intuition is inline with inconsistent policy repair of Definition 9, since we know that the encrypted values have already been outputted and publishing the key releases them as well, we should either explicitly add Secret → Public to the policy, or use Definition 9 to update the policy.

6. Verification of Dynamic Policies

This section discusses the precise verification of dynamic policies by symbolic execution and automated theorem proving. Our verification approach operates in two phases: (1) it extracts the dependencies of a source program by means of symbolic execution and (2) it verifies the security conditions for dynamic policies under different attacker models by relying on an SMT solver. We impose some restrictions on the source program to make the analysis in (1) feasible. First, we assume a bounded model of runtime behavior, hence programs always terminate. Second, we assume all inputs from external environments can be read at the beginning. Hence, to support programs with inputs, one can assign fresh variables to each of the elements of a (finite) input stream. The output of phase (1) is a graph capturing dependencies between program inputs and outputs. We refer to existing works for details on symbolic execution [24].

Specifically, we analyze source programs symbolically to extract precise dependencies between program inputs and outputs. Observe that this information is sufficient to reason about security because security policies refer to program inputs and attacker observations are made through program outputs. For each program output, our symbolic analysis stores a path condition $P_c \in PC$ and an output expression $e \in \mathcal{E}$x which are defined over the program inputs. The path condition is a predicate that represents the set of initial concrete values that trigger the execution of an output expression $e$. In particular, any satisfying assignment $\delta$ of path condition $P_c$ determines a concrete program output as computed by $\delta(e)$.

We represent these dependencies in the form of symbolic output trees (SOT) consisting of: (a) a set of nodes $B$ labeled with output expressions $e \in \mathcal{E}xp$; (b) a set of control flow edges $E \subseteq B \times B$; (c) a set of path conditions $P_c$; (d) a mapping from nodes to output expressions $O : B \mapsto \mathcal{E}xp$; (e) a mapping from edges to path conditions $L : E \mapsto PC$; and (f) a root node Start. We also extend the SOT with a special node End, in order to make terminal states explicit in the construction. Figure 3 illustrates the SOT of Program 12. Node $n$3 indicates that for all initial values of variable $y$ such that $y \leq 0$, the second output of the program is the expression 2.

We define security policies with respect to an attacker at security level $A$. For a program variable $x$ such that $X \rightarrow A$, we denote its initial value by $l$ (for low) to reflect that variable $x$ can be observed by $A$, otherwise we denote it by $h$ (for high). We lift this notation to tuples of input variables $\vec{t}$ and $\vec{h}$ in the expected manner. Moreover, we support fine-grained policies modeled by predicates $\phi$ over initial values of variables. We define the policy $P$ over $\vec{t}$, $\vec{h}$, written as $P(\vec{t}, \vec{h})$ by the predicate:

$$\vec{t} = \vec{t}^\prime \land \phi \quad (4)$$

where $\vec{t}^\prime$ stands for the names of low variables, and predicate $\phi$ represents the leaked (i.e., declassified) expressions which is defined over low and high identifiers, and their names. The policy predicate $P(\vec{t}, \vec{h})$ induces an equivalence relation $[\sigma]_A^\prime$ over initial stores $\sigma$, which corresponds to the policy knowledge (cf. Section 4.1). The relation can be constructed as follows: Let $\sigma$ and $\sigma'$ be two program stores over program variables and their names, respectively, $\text{unprime}(S)$ be an operator “undoing” the variable names over a set $S$, and $q(\sigma)(\sigma')$ be the evaluation of a predicate $q$ over $\sigma$ and $\sigma'$. Then the equivalence relation $[\sigma]_A^\prime = \text{unprime}(\{\sigma' | P(\vec{t}, \vec{h})\}(\sigma)(\sigma'))$ defines the policy knowledge induced by the predicate $P(\vec{t}, \vec{h})$.

For example, the policy in line 1 of Program 12 means that variable $x$ is low, variable $y$ is high, and expression $y > 0$ is leaked. Following equation (4), we write the policy $P(x, y)$ as $x = x', y > 0 = y' > 0$.

A satisfying assignment is a mapping from the free variables of $P_c$ to values, which makes the predicate $P_c$ evaluate to true.
We remark that the policy \( P(\vec{T}, \vec{h}) \) corresponds to a
global static policy encoding of a standard declassification
policy \( \phi \) [25]. In fact, prior work by Balliu et al. [18]
shows how a static policy \( P(\vec{T}, \vec{h}) \) can be verified
against an SOT by means of an SMT solver. Definition
10 presents the process of generating such a formula.

**Definition 10.** An SOT \( S \) is secure wrt. a security policy
\( P(\vec{T}, \vec{h}) \) iff the following formula is unsatisfiable:

\[
P(\vec{T}, \vec{h}) \land \bigwedge_{n \in N(S)} \left( P_{cn}(\vec{T}, \vec{h}) \land \Big( \bigwedge_{n' \in N(S)} \neg\left(P_{cn'}(\vec{T}, \vec{h}') \land \vec{O}_n(\vec{T}, \vec{h}) = \vec{O}_{n'}(\vec{T}, \vec{h}')\right) \right)\]

where \( \vec{O}_n \) is the tuple of output expressions along the SOT
path to node \( n \). \( \vec{O}_n = \vec{O}_{n'} \) denotes the component-wise
equality of two tuples, and \( N(S) \) is the nodes of \( S \).

Definition 10 presents a logical encoding of our security
condition \( p \leq k_i \) of Section 4 for the perfect recall
attacker and a static policy \( p \). Specifically, the condition is true
if all initial stores that satisfy policy \( p \) are contained
in the attacker’s knowledge set \( k_i \) at each program point \( i \).
We focus only on program outputs, since non-observable
commands do not affect knowledge. The non-satisfiability
of the formula above implies that for any initial state
\((\vec{T}, \vec{h})\) that satisfies the policy \( P(\vec{T}, \vec{h}) \) and reaches
some output node \( n \) (i.e., \( n \in N(S) \) and \( P_{cn}(\vec{T}, \vec{h}) \))
yielding an output sequence \( \vec{O}_n \), it is impossible to find
another state \((\vec{T}', \vec{h}')\) that satisfies the policy and reaches
some output node \( n' \) (i.e., \( n \in N(S) \) and \( P_{cn}(\vec{T}', \vec{h}') \))
yielding a different output sequence \( \vec{O}_{n'} \). Consequently,
for any initial store \((\vec{T}, \vec{h})\) \in \( P(\vec{T}, \vec{h}) \), we have that
\((\vec{T}, \vec{h}) \in k_i \), thus verifying the security condition. By
contrast, if the formula is satisfiable, there exist two stores
that satisfy the policy \( P(\vec{T}, \vec{h}) \), but either one store
does not reach the output node or the two stores produce
different output sequences. This implies that there is an
initial store \((\vec{T}, \vec{h})\) \in \( P(\vec{T}, \vec{h}) \), such that \((\vec{T}, \vec{h}) \notin k_i \),
thus violating the security condition.

For example, the SOT of Figure 3 is secure wrt.
the above-mentioned policy \( P(x, y) \), as witnessed by the
following unsatisfiable formula:

\[
x = x' \land (y > 0 = y' > 0) \land \bigwedge_{n \in N(S)} \left( P_{cn}(x, y) \land \left( \bigwedge_{n' \in N(S)} \neg\left(P_{cn'}(x, y') \land \vec{O}_n(x, y) = \vec{O}_{n'}(x, y')\right) \right) \right)\]

We revise this condition to verify deterministic pro-
grams with dynamic policies for our attacker models. In a
dynamic setting, the active policy at each node of \( S \) might
be different from its parent or children. Therefore, instead
of generating a single formula for the whole SOT, we need
to generate a formula for every node \( n \) corresponding
to its policy \( P_n(\vec{T}, \vec{h}) \). To this end, we modify the
SOT generation algorithm and enrich each node with an
additional attribute to store the active policy at the time
of its creation.

**6.1. Perfect Recall Attacker**

We use Definition 11 to check the security of a pro-
gram wrt. the perfect recall attacker.

**Definition 11.** An SOT \( S \) secure wrt all \( n \in N(S) \)
with active policy \( P_n(\vec{T}, \vec{h}) \), the following formula is
unsatisfiable:

\[
P_n(\vec{T}, \vec{h}) \land \left( P_{cn}(\vec{I}_n, \vec{h}_n) \land \bigwedge_{n' \in N(S)} \neg\left(P_{cn'}(\vec{I}_n, \vec{h}_n') \land \vec{O}_n(\vec{I}_n, \vec{h}_n) = \vec{O}_{n'}(\vec{I}_n, \vec{h}_n')\right) \right)\]

In contrast to Definition 11 here the active policy can be
different in each node (as denoted by \( P_{cn}(\vec{I}_n, \vec{h}_n) \)). For
a node \( n \) the formula is unsatisfiable only if there is no
other node with a satisfiable path condition \( P_{cn'}(\vec{I}_n, \vec{h}_n') \)
that can produce a different output. Unsatisfiability of the
formula for a node \( n \) means that the program is secure
wrt. the active policy at that node. To ensure security for
the SOT we repeat this process for all nodes, regenerate
the formula at each node and check its satisfiability. If none
of the formulas are satisfiable, we can conclude that
the SOT \( S \) is secure.

We use a similar approach to verify the policy con-
istency. However, because we do not have specific nodes
for policy changes, we mark all of the nodes that appear
right after a policy change and only check the policy
consistency on those nodes using the following definition:
Definition 12. Given an SOT $S$, active policy $P_n(\overrightarrow{t}, \overrightarrow{h})$, and parent$(n)$ which returns the parent of node $n$, a policy change is consistent iff for all $n \in N(S)$ such that $n$ comes right after a policy change, the following formula is unsatisfiable:

$$P_n(\overrightarrow{t}, \overrightarrow{h}) \land \left( \neg \left( P_{\text{parent}}(n)(\overrightarrow{t}_n, \overrightarrow{h}_n) \land \left( \bigwedge_{n' \in N(S)} \neg \left( P_{n'}(\overrightarrow{t}_{n'}, \overrightarrow{h}_{n'})(\overrightarrow{t}_{n'} = \overrightarrow{t}_n) \land \overrightarrow{h}_{n'} = \overrightarrow{h}_n \right) \right) \right) \right)$$

If a node was marked as an output after a policy change, before checking its security using Definition 11, we first use Definition 12 to check the policy consistency. The process is similar to Definition 11, except that here instead of using the path condition and output of node $n$, we use the path condition and output of its parent ($P_{\text{parent}}(n)(\overrightarrow{t}_n, \overrightarrow{h}_n)$ and $\overrightarrow{O}_{\text{parent}}(n)(\overrightarrow{t}_n, \overrightarrow{h}_n)$, respectively).

Following Definition 2 in Section 4, we check that the attacker knowledge is allowed by the new policy. If node $n$ is marked by the policy change it means that a policy change has happened between $n$ and parent$(n)$, so we use the output of the node before the policy change (parent node) $\overrightarrow{O}_{\text{parent}}(n)(\overrightarrow{t}_n, \overrightarrow{h}_n)$ and the new policy (policy of the current node) $P_n(\overrightarrow{t}, \overrightarrow{h})$ to generate the formula, and check that the new policy is in line with the observations up to $n$'s parent. The unsatisfiability of this formula means that the policy change between nodes parent$(n)$ and $n$ is consistent.

Figure 4 illustrates the SOT of Program 13. As in the previous example, a node with expression $x$ represents outputting the initial value of $x$ (with $P_c = \text{true}$), while $y > 0$ and $y \leq 0$ are path conditions. The nodes following a policy change are shown with dashed lines (nodes $n1$ and $n5$). This program is rejected by the Definition 12, because the policy change between nodes $n3$ and $n5$ is inconsistent. The generated formula for node $n5$ is:

$$\left( P_{n3}(\emptyset, \{x, y\}) \land \left( \bigwedge_{n' \in N(S)} \neg \left( P_{n'}(\emptyset, \{x', y'\}) \right) \right) \right)$$

The path condition of node $n3$ is true and its output sequence is $O_{n3} = (x, 1, 1)$. The formula is satisfiable if there exists a value for $y$ or $x$ where $P_{n3}(y)$ holds and for all nodes falsifies either the path conditions or the equality between outputs. The only node on the same level as $n3$ is $n3$ itself, which clearly means that the path condition is also true. However, since the output sequences are $(x, 1, 1)$ and $(x', 1, 1)$, it is sufficient to pick any value for $x$ and $x'$ such that $x' \neq x$ to satisfy the following formula. This implies that the policy change at node $n5$ is inconsistent.

$$\left( \text{true} \land \neg \left( \text{true} \land (x, 1, 1) = (x', 1, 1) \right) \right)$$

The following theorems show soundness of Definition 11 and Definition 12 w.r.t. the security conditions of Definition 3 and Definition 2, respectively.

Theorem 2. Given a SOT $S$, if the formula in Definition 11 is unsatisfiable for all nodes $n \in S$, then $S$ satisfies Definition 3.

Theorem 3. Given a SOT $S$, if the formula in Definition 12 is unsatisfiable for all nodes $n \in S$ such that $n$ follows a policy change, then $S$ satisfies Definition 2.

6.2. Forgetful Attacker

In line with the definitions of forgetful attackers in Section 4, we ignore the actual values of the output expressions occurring before the last policy change. Therefore, the output tuple $\overrightarrow{O}_{frg}$ for the forgetful attacker replaces all of the outputs that occurred before the last policy change with the constant value 1. Additionally, while generating the inner conjunction of the formula, we only consider the nodes that have the same number of policy changes as $n$, using the auxiliary function $\text{sameNP}(S, n)$. Definition 13 adapts Definition 11 for forgetful attackers:

Definition 13. Given an SOT $S$, policy $P_n(\overrightarrow{t}, \overrightarrow{h})$ at node $n$, $S$ is secure wrt. forgetful attacker iff for all $n \in N(S)$, the following formula is unsatisfiable:

$$P_n(\overrightarrow{t}, \overrightarrow{h}) \land \left( P_{n}(\overrightarrow{t}_{n}, \overrightarrow{h}_{n}) \land \left( \bigwedge_{n' \in \text{sameNP}(S,n)} \neg \left( P_{n'}(\overrightarrow{t}_{n'}, \overrightarrow{h}_{n'})(\overrightarrow{t}_{n'} = \overrightarrow{t}_n) \land \overrightarrow{h}_{n'} = \overrightarrow{h}_n \right) \right) \right)$$

It uses $\overrightarrow{O}_{frg}$ to compute output sequences, ignoring the values leaked before the policy change. Additionally, it only generates the formula for the nodes with the same number of policy changes. This is because the only relevant nodes for a forgetful attacker are the ones that are on the same epoch as the current node. Progress leaks are captured by the number of constant values in $\overrightarrow{O}_{frg}$ and the actual values leaked in the other epochs are ignored.

To illustrate this process, we revisit Program 7 and its SOT in Figure 5, and check the security for the forgetful attacker using Definition 13. For example, at node $n5$ the generated formula is:

$$\left( P_{n5}(\emptyset, x) \land \left( \bigwedge_{n' \in \text{sameNP}(S,n)} \neg \left( P_{n'}(\emptyset, x') \land \overrightarrow{O}_{frg, n5}(\emptyset, x) = \overrightarrow{O}_{frg, n5}(\emptyset, x') \right) \right) \right)$$

The path condition of node $n5$ is $x > 0$ and its output sequence is $\overrightarrow{O}_{n5} = (\text{true}, \text{true}, 1)$. The formula is satisfiable if there exists a value for $x$ where $P_{n5}(x)$ holds, and for all nodes it falsifies either the path condition or the equality between outputs. The only node with the same number of policy changes and at the same level as $n5$ is $n5$ itself. This clearly means that the output sequences are equal. Therefore, to satisfy the formula we need a value $x'$ that falsifies the path condition $x' > 0$, which can be any non-positive value. Thus, the formula is satisfiable and the program is insecure.
Theorem 4 shows the soundness of Definition 13 wrt. the security condition for the forgetful attacker.

**Theorem 4.** Given a SOT $S$, if the formula in Definition 13 is unsatisfiable for all nodes $n \in S$, then $S$ satisfies Definition 3 for the forgetful attacker.

We refer to Appendix C for proof sketches of the theorems, and Appendix A for the verification algorithm of bounded memory attackers.

### 6.3. Policy Repair

This section we discuss an approach for generating repair policies. As discussed in Section 4.3, a repair policy should ideally be the intersection between attacker knowledge and the new inconsistent policy. The approach presented here leverages the information provided by the SOT to calculate the attacker’s knowledge at node $n$ as a combination of the direct (outputs) and indirect ($P_c$) values observations made by the attacker. However, this approach does not always result in the intersection as defined by Definition 9 as it sometimes over-approximates the attacker’s knowledge. Developing a precise approach for generating consistent policies is left for future work.

When the policy consistency check fails at some node $n$, we can calculate the knowledge by traversing the SOT from $n$ up to node $\text{start}$ and collecting the attacker’s explicit observations (i.e., the output expressions) and implicit observation (i.e., $P_c$s). It is important to note that not all output expressions and $P_c$s leak information, therefore we should only collect the ones that are leaking some information. Here we achieve this by applying a preprocessing step to the SOT, which uses a bounded memory attacker with memory capacity of $m = 1$ to determine the leaked expressions at each level of SOT. The addition of these leaked expressions to the new policy gives a candidate repaired policy.

The intuition behind this approach is that a new policy can only be inconsistent if it is more restrictive than the current policy. Thus a repaired policy should ease some of those restrictions. To this end, we extract already leaked expressions and add them to the inconsistent policy, which gives us the most restrictive version of policy that is consistent with the knowledge. After generating the repaired policy, we should also update the policy field of $n$’s children up to the next policy change. This is because all of the nodes between $n$ and the ones with a new policy are affected by the inconsistent policy.

### 7. Implementation and Evaluation

We implemented the algorithms presented in Section 6 by extending ENCoVER [26] and creating a prototype dubbed DYnCoVER [20]. Like ENCoVER, DYnCoVER relies on Symbolic PathFinder (SPF) [27], an extension of Java PathFinder (JPF) [28], to concolically execute programs and extract the symbolic output trees from Java bytecode.

DYnCoVER analyzes the program by means of concolic testing and does the following in a loop to explore all execution paths of the program and generate the SOT: it starts with concrete and symbolic values for input variables and executes the program concolically to collect each step’s path condition. These conditions are then passed to a constraint solver to generate new inputs that explore different paths. Upon reaching an output statement, the output expression is evaluated in the symbolic state and a new node representing the result of that evaluation is added to the SOT. The path condition that directed the program to this output statement is also saved in the node.

After generating the SOT, DYnCoVER traverses the tree using a depth-first search (DFS) strategy, and for each node, depending on the attacker, it generates the formulas described in Section 6. Then, DYnCoVER feeds the generated formula to a satisfiability modulo theory (SMT) solver (Z3 in the current implementation). If the SMT solver answers that the formula is satisfiable, then the analyzed program is deemed insecure. DYnCoVER repeats this process for all of the nodes in SOT and if the SMT solver’s answer was unsatisfiable for all nodes, the program is accepted as secure.

For the perfect recall and bounded memory attackers, DYnCoVER also checks the policy consistency for all nodes that are marked as “nodes following a policy change”. DYnCoVER uses Definition 12 for generating the policy consistency check formula, feeds it to the SMT solver, and if the result was unsatisfiable, it deems the policy change as consistent, and moves on to checking the security on that node.

DYnCoVER also supports policy repair by relying on the heuristic of Section 6.3. If configured in repair mode, DYnCoVER performs preprocessing on the SOT and identifies leaking expressions. Upon reaching an inconsistent policy, it shows a warning message, proceeds to generate the repaired policy, and prints it to the user.

DYnCoVER uses ENCoVER [26] as a basis and extends it with support for dynamic policies, policy consistency checks, and policy repair. DYnCoVER is approximately 6 KLOC as computed by CLOC and includes nearly 86 classes/interfaces. Like ENCoVER, the class of programs that DYnCoVER can handle is indirectly limited by the class of programs SPF (JPF core and its symbolic extension) can handle and the class of constraints Z3 can solve.

### 7.1. Case Studies

To evaluate the effectiveness and efficiency of DYnCoVER, we carried out two different experiments. First, we created a micro benchmark suite to facilitate checking and understanding dynamic policy scenarios and different
types of attackers. Second, we implemented and verified the core of a social network to demonstrate the effectiveness of our security conditions in a real-world scenario.

These case studies target three objectives: (1) to validate that the results of DYNCOVER are in line with the conditions in Section 4; (2) to ensure that the policy repair heuristic works as expected; (3) to evaluate the performance of DYNCOVER.

7.1. Benchmark. Our benchmark consists of 25 programs, including programs from the paper, to demonstrate different aspects of dynamic policies. It includes programs with various constructs, loops, and implicit leaks. This benchmark is implemented in Java, and the only use of non-standard command is the setPolicy method, indicating a policy change. Each program has a configuration file which defines the attacker type, its memory capacity, and the method used to deal with inconsistent policies. These .jpf configuration files are used by JPF’s virtual machine and DYNCOVER to verify the program.

Table 1 shows an excerpt of programs from the benchmark, Table 3 in the Appendix contains more programs. As we can see in column “DYNCOVER Result”, DYNCOVER rejects insecure programs and accepts secure ones, in line with the definitions in Section 4. In addition to the results for security and policy consistency, Table 1 also reports some information about the efficiency and performance of DYNCOVER. For simple programs with small number of outputs, the SOT size and the evaluation time of DYNCOVER is low. But when testing more complex programs with multiple loops and outputs, the performance decreases. Memory usage of DYNCOVER is around 235 MB for simple programs, and starts to increase when the number of loops and instructions increases.

7.1.2. Social Network. In this case study, we implemented a social network that simulates the interactions between users, and contains some of the main functionalities of a social network, such as following, unfollowing, blocking other users, sending DMs, and creating groups and events. Users also have privacy settings and change their setting to hide their sensitive information such as phone number. The high level of interactivity between entities in a social networks makes it a good candidate for dynamic policy analysis.

A social network is naturally an interactive program, whose behavior is determined by the actions of different users of the system. To model these behaviors and make them amenable to extract the SOT of the program with DYNCOVER, we implemented an additional program which simulates the behavior of different users involved in the execution of the interactive program.

The Java implementation of the social network has 5 classes and 659 LOCs. There is one class for each of the entities: server, user, group, event, and post. To evaluate this case study, 6 different scenarios have been implemented and examined. The results of these experiments are reported in Table 2.

In the postForFollowers scenario, users interact by following each other and creating posts. The goal here is to ensure that a post is only visible to the followers of a certain user. This scenario is secure for a forgetful attacker, and inconsistent for a perfect recall attacker. This is because the ex-follower has already seen some of the unfollowed user’s posts. The second scenario is similar, but this time a user can block their followers. Similarly, this program is secure for a forgetful attacker and inconsistent for a perfect recall attacker. The policy repair mode does not make sense for these scenarios, because after unfollowing or getting blocked, the observer should no longer be able to see the user’s old posts.

The next scenario simulates forwarding a user’s DM to another user. This scenario is insecure for all types of attackers, because a third user should not be able to see other users’ DMs. The phoneNumberPrivacy scenario checks the privacy settings of a user. Initially, the user’s information such as the phone number is private. However, a user can changes their privacy setting to make the phone number public. The goal here is to make sure that users cannot see other users’ private information. This scenario is secure for both perfect recall and forgetful attackers.

Next, we consider a scenario in which a user’s membership in a group should be kept secret from all users that are not in that group. A user cannot see the group members until they are added to that group. This scenario is secure for all three types of attackers. Now, if we change this scenario in such a way that a users leaves the group after learning the names of its members, then the program is inconsistent for perfect recall and secure for forgetful attackers. In the last scenario we consider events. Here a user should not be able to see an event’s information such as its title or date unless they are invited to it. The program is secure for this scenario.

8. Related Work

This section discusses closely related works targeting dynamic policies and information flow control. We refer to Broberg et al. [11] for a survey on dynamic policies.

Our security framework is inspired by the work of Askarov and Chong [8] on knowledge-based security conditions for dynamic policies. They propose a general framework for capturing the semantics of dynamic policies for all attackers, showing that secure program under perfect recall attacker can be insecure under a weaker attacker. We revisit and extend their framework to accommodate three realistic attacker models and point out the challenges with policy consistency. Because the notions of perfect recall attacker and bounded memory attackers have well-defined interpretations in applications and epistemic logics [29], security conditions should be specific about the attacker model and uncover inconsistent policies. This allows us to show that the security of a program under a stronger attacker implies security under weaker attackers. Moreover, we propose a security condition for forgetful attackers to capture transient release of sensitive information, instantiating the framework of Askarov and Chong. On the enforcement side, DYNCOVER uses automated theorem proving while Askarov and Chong design a security type system, each targeting well-known trade-offs between precision and scalability. Van Deft et al. [10] improve the framework of Askarov and Chong with regards to progress-insensitive security, showing how a type system enforces security against all attackers. By contrast, our conditions are progress sensitive, while progress insensitivity can be accommodated
TABLE 1: Benchmark evaluation results

<table>
<thead>
<tr>
<th>Program</th>
<th>DYNCOVER Result</th>
<th>Attacker Type</th>
<th>Inconsistent Policy Mode</th>
<th>JPF Inst</th>
<th>Time (ms)</th>
<th>SOT Nodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Program 1</td>
<td>✓</td>
<td>Perfect</td>
<td>Reject</td>
<td>2940</td>
<td>219.5</td>
<td>8.7</td>
</tr>
<tr>
<td>Program 2</td>
<td>✔</td>
<td>Perfect</td>
<td>Repair</td>
<td>2940</td>
<td>231.6</td>
<td>8.8</td>
</tr>
<tr>
<td>Program 3</td>
<td>✔</td>
<td>Forgetful</td>
<td>Reject</td>
<td>2940</td>
<td>217.4</td>
<td>8.7</td>
</tr>
<tr>
<td>Program 4</td>
<td>×</td>
<td>Perfect</td>
<td>Reject</td>
<td>2964</td>
<td>316.4</td>
<td>38.4</td>
</tr>
<tr>
<td>Program 5</td>
<td>×</td>
<td>Bounded</td>
<td>Reject</td>
<td>2964</td>
<td>301.0</td>
<td>38.6</td>
</tr>
<tr>
<td>Program 6</td>
<td>×</td>
<td>Forgetful</td>
<td>Reject</td>
<td>2982</td>
<td>288.2</td>
<td>38.5</td>
</tr>
<tr>
<td>Program 13</td>
<td>✓</td>
<td>Perfect</td>
<td>Reject</td>
<td>2982</td>
<td>292.7</td>
<td>89.5</td>
</tr>
<tr>
<td>Program 13</td>
<td>✓</td>
<td>Perfect</td>
<td>Repair</td>
<td>2982</td>
<td>307.1</td>
<td>49.0</td>
</tr>
<tr>
<td>Program 13</td>
<td>✓</td>
<td>Bounded</td>
<td>Reject</td>
<td>2982</td>
<td>341.6</td>
<td>47.0</td>
</tr>
<tr>
<td>Program 13</td>
<td>✓</td>
<td>Forgetful</td>
<td>Reject</td>
<td>2982</td>
<td>300.0</td>
<td>48.6</td>
</tr>
</tbody>
</table>

DYNCOVER Results: ✓ the program is secure; × the program is insecure; ‡ the program has an inconsistent policy change.
Inconsistent Policy: What to do when facing an inconsistent policy: Reject the inconsistent policies; Repair the policy.
JPF Inst: total number of instructions executed by JPF
Time: OA: overall; ME: model extraction; FG: interference formula generation; FS: interference formula satisfiability checking; PR: policy repair (only if applicable)
SOT Nodes: Number of nodes in the generated Symbolic Output Tree

TABLE 2: Social network evaluation results

<table>
<thead>
<tr>
<th>Program</th>
<th>DYNCOVER Result</th>
<th>Attacker Type</th>
<th>Inconsistent Policy Mode</th>
<th>JPF Inst</th>
<th>Time (ms)</th>
<th>SOT Nodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>postForFollowers</td>
<td>✗</td>
<td>Perfect</td>
<td>Reject</td>
<td>13953</td>
<td>69.5</td>
<td>2.7</td>
</tr>
<tr>
<td>postForFollowers</td>
<td>✓</td>
<td>Forgetful</td>
<td>Reject</td>
<td>13953</td>
<td>79.5</td>
<td>6</td>
</tr>
<tr>
<td>blockingUser</td>
<td>✗</td>
<td>Perfect</td>
<td>Reject</td>
<td>14133</td>
<td>69.6</td>
<td>2.7</td>
</tr>
<tr>
<td>blockingUser</td>
<td>✓</td>
<td>Forgetful</td>
<td>Reject</td>
<td>14133</td>
<td>59.9</td>
<td>6</td>
</tr>
<tr>
<td>forwardingDM</td>
<td>×</td>
<td>Perfect</td>
<td>Reject</td>
<td>13037</td>
<td>51.9</td>
<td>169.5</td>
</tr>
<tr>
<td>forwardingDM</td>
<td>×</td>
<td>Bounded</td>
<td>Reject</td>
<td>13037</td>
<td>49.5</td>
<td>166.8</td>
</tr>
<tr>
<td>forwardingDM</td>
<td>×</td>
<td>Forgetful</td>
<td>Reject</td>
<td>13037</td>
<td>49.5</td>
<td>164.4</td>
</tr>
<tr>
<td>phoneNumberPrivacy</td>
<td>✓</td>
<td>Perfect</td>
<td>Reject</td>
<td>13135</td>
<td>69.6</td>
<td>2.7</td>
</tr>
<tr>
<td>phoneNumberPrivacy</td>
<td>✓</td>
<td>Forgetful</td>
<td>Reject</td>
<td>13135</td>
<td>680.7</td>
<td>212.7</td>
</tr>
<tr>
<td>leakMembership</td>
<td>✓</td>
<td>Perfect</td>
<td>Reject</td>
<td>18569</td>
<td>74.7</td>
<td>296.8</td>
</tr>
<tr>
<td>leakMembership leave</td>
<td>✓</td>
<td>Perfect</td>
<td>Reject</td>
<td>18850</td>
<td>802.2</td>
<td>314.9</td>
</tr>
<tr>
<td>leakMembership leave</td>
<td>✓</td>
<td>Forgetful</td>
<td>Reject</td>
<td>18850</td>
<td>769.0</td>
<td>301.8</td>
</tr>
<tr>
<td>leakEventInfo</td>
<td>✓</td>
<td>Perfect</td>
<td>Reject</td>
<td>10676</td>
<td>427.5</td>
<td>159.5</td>
</tr>
</tbody>
</table>

following Van Deft et al. [10]. Broberg et al. [11] illuminate the different facet of dynamic policies proposed in the literature [30], [12], [13], [14], [16], [9], [21]. We revisit and discuss this facets in our framework by developing the corresponding security conditions or pointing out mismatches. Other works addressing the challenge of flexible policies include Chudnov and Naumann [31] framework for downgrading policies in reactive programs, Lu and Zhang’s [32] framework for non-transitive policies, and Kozyri and Schneider’s [33] reactive labels.

Recently, Li and Zhang [34] propose a general-purpose framework for dynamic policies. Their approach categorizes dynamic policies into persistent and transient policies, and uses the notion of effective traces to define a unified knowledge-based security condition. By contrast, our work departs from existing works on dynamic policies, by focusing on an attacker-centric approach and tries to address the issues of dynamic policies through policy consistency and the relation between attacker power and policy.

Our enforcement techniques build on the line of work on verifying static information flow policies by automated theorem proving [17], [19], [18], [35], [36]. To our best knowledge, none of these works addresses either dynamic policies or the issues of policy consistency and policy repair. A precursor of our approach is the work of Balliu et al. [18] which also uses Java Pathfinder to extract program dependencies and verify static noninterference policies by symbolic execution. Our verification conditions are similar to Balliu et al. [18] for static policies, and develop them further to accommodate dynamic policies. Paragon [37] extends Java with support for dynamic policies using a security type system [16], [38] and it enforces security for the perfect recall attacker. By contrast, DYNCOVER additionally supports bounded memory and forgetful attacker models with policy consistency and repair. Other languages and tools supporting information flow control for perfect recall attackers include JIF [39], LIO [40], Jeeves [41], and JOANA [42].

9. Conclusion

We have revised knowledge-based security conditions for dynamic policies and proposed attacker-centric conditions for perfect recall, bounded memory, and forgetful attackers. Drawing on the notion of policy consistency, we studied the relationship with the different facets of dynamic policies as well as policy repair. To verify and repair dynamic policies under different attacker models, we designed, implemented, and evaluated DYNCOVER, an open source tool based on symbolic execution and SMT solving. An interesting avenue for future work is to investigate the interplay between integrity and confidentiality for dynamic policies [43], [44], [45], [46], [47].

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References


[3] ——, “Tight enforcement of information-release policies for dy-


[8] A. Askarov and S. Chong, “Learning is change in knowledge:
Knowledge-based security for dynamic policies,” in CSF. IEEE,

programs,” in NordSec, 2013.


of information-flow policies,” in FCS, 2005.

updates in security-typed languages,” in CSF Workshop. IEEE,

Declassification Policies and Modular Static Enforcement,” in S&P,

2009.


exploration for information flow security,” in CSF. IEEE, 2012,
pp. 30–44.


[21] M. Guarnieri, M. Balliu, D. Schoepe, D. Basin, and A. Sabelfeld,
“Information-flow control for database-backed applications,” in
EuroS&P. IEEE, 2019, pp. 79–94.

[22] A. Askarov, S. Hunt, A. Sabelfeld, and D. Sands, “Termination-
sensitive noninterference leaks more than just a bit,” in ESORICS.

[23] D. Clark and S. Hunt, “Non-interference for deterministic interac-

symbolic execution and invariant generation,” in Model Checking


Mehlitz, and N. Rungta, “Symbolic pathfinder: integrating sym-
bolic execution with model checking for java bytecode analysis,”


[31] A. Chudnov and D. A. Naumann, “Assuming you know: Epistemic
semantics of relational annotations for expressive flow policies,” in

[32] Y. Lu and C. Zhang, “Nontransitive security types for coarse-
grained information flow control,” in CSF. IEEE, 2020, pp. 199–
213.

[33] E. Kozyri and F. B. Schneider, “RIf: Reactive information flow

[34] P. Li and D. Zhang, “Towards a general-purpose dynamic infor-

[35] D. Milushev, W. Beck, and D. Clarke, “Noninterference via sym-
bolic execution,” in Formal Techniques for Distributed Systems.

[36] Q. H. Do, R. Bubel, and R. Hähnle, “Automatic detection and
demonstrator generation for information flow leaks in object-
oriented programs,” computers & security, vol. 67, pp. 335–349,
2017.

[37] N. Broberg, B. van Delft, and D. Sands, “Paragons - practical
programming with information flow control,” J. Comput. Secur.,

[38] N. Broberg and D. Sands, “Paralocks: role-based information flow

[39] A. C. Myers, “Jflow: Practical mostly-static information flow con-

dynamic information flow control in haskell,” in SIGPLAN, 2011,
pp. 95–106.

automatically enforcing privacy policies,” in POPL, 2012, p. 8596.

[42] G. Snelting, D. Giffhorn, J. Graf, C. Hammer, M. Hecker, M. Mohr,
and D. Wasserrab, “Checking probabilistic noninterference using

[43] A. Myers and A. Askarov, “Attackor control and impact for con-
fidentiality and integrity,” Logical Methods in Computer Science,
vol. 7, 2011.


[47] E. Cecchetti, A. C. Myers, and O. Arden, “Nonmalleable informa-

Appendix A.

Bounded Memory Attacker

The unlimited memory of perfect recall attacker means
that it can remember everything it once observed. A
bounded memory attacker is a variant of perfect recall
attacker with a limited memory (called m hereafter). After
observing m outputs, its memory will become full and in
order to capture any new outputs the oldest observation
should be removed from it (in a FIFO manner).

[54] A. Askarov, S. Hunt, A. Sabelfeld, and D. Sands, “Gradual release: Unifying declas-
A.1. Security Policies

The security condition used for bounded memory attacker is similar to Definition 4, except that when computing the knowledge of a bounded memory attacker, we have to consider its memory capacity \( (m) \) as well as the number of outputs it has observed. If the number of outputs is less than \( m \), the attacker is going to behave just like perfect recall, and if it is more than \( m \), the attacker is going to only remember the last \( m \) observations.

With this intuition, we can define the auxiliary function \( \text{suffix}(t,m) \) which takes a trace \( t \) and returns the last \( m \) events of the trace:

**Definition 14.** Given trace \( t \) as \( t = \alpha_1, \alpha_2, ..., \alpha_k \), \( \text{suffix}(t,m) \) is defined as:

\[
\text{suffix}(t,m) = \begin{cases} 
  t & \text{if } k \leq m \\
  \alpha_{k-m}, ..., \alpha_k & \text{if } k > m 
\end{cases}
\]

Now, we can define the knowledge of a bounded memory attacker at execution point \( i \):

**Definition 15.** Program \( c \) with initial store \( \sigma \), and initial policy \( P_{\text{init}} \) produces trace \( t \) after \( i \) execution steps, i.e., \( \langle c, \sigma, P_{\text{init}} \rangle \rightarrow_i t \). We write \( k^\text{bnd}(c, \sigma, P_{\text{init}}, A, m) \) for the knowledge of an attacker that observes the outputs of this program on channel \( A \) and has a bounded memory capacity of \( m \) length, and define it as follows:

\[
k^\text{bnd}_i(c, \sigma, P_{\text{init}}, A, m) = \{ \sigma' \mid \langle c, \sigma, P_{\text{init}} \rangle \rightarrow_j t \}
\& \text{suffix}(t|_A, m) = \text{suffix}(t'|_A, m) \}
\]

By adapting Definitions 2 and 3 to \( k^\text{bnd}(c, \sigma, P_{\text{init}}, A, m) \) for attacker knowledge, we can use Definition 4 to check security for bounded memory attackers as well.

A.2. Verification of Dynamic Policies

Since a bounded memory attacker is a special type of perfect recall with limited observations, the verification approach used for checking a program’s security against a bounded attacker is also similar to the verification for a perfect recall attacker. We just have to modify Definition 11 to account for the limited memory of the attacker.

**Definition 16.** Given an SOT \( S \), active policy \( P_n(\overrightarrow{t}, \overrightarrow{h}) \) at node \( n \), \( S \) is secure wrt. bounded memory attacker with memory capacity \( m \) iff for all nodes \( n \in N(S) \), the following formula is unsatisfiable:

\[
P_n(\overrightarrow{t}, \overrightarrow{h}) \land \left( P_{c_n}(\overrightarrow{t}, \overrightarrow{h}) \land \left( \bigwedge_{n' \in N(S)} \neg (P_{c_{n'}}(I_{n'}, \overrightarrow{h'})) \right) \right) = \bigwedge_{n' \in N(S)} \left( P_{c_{n'}}(I_{n'}, \overrightarrow{h'}) \land \overrightarrow{O}^{m}_{n'}(I_{n'}, \overrightarrow{h'}) \right)
\]

where \( \overrightarrow{O}^{m}_{n} \) is a tuple of the last \( m \) output expressions encountered on a path in SOT from node Start to node \( n \), \( \overrightarrow{O}^{m}_{n} = \overrightarrow{O}^{m}_{n'} \) denotes the component-wise equality between two tuples, and \( N(S) \) is the nodes of SOT \( S \).

In this definition we limit the length of the attacker’s observations by \( m \), which is the capacity of his memory. In other words, \( \overrightarrow{O}^{m}_{n} \) contains the last \( m \) outputs observable by the attacker. Therefore by checking \( \overrightarrow{O}^{m}_{n'}(I_{n'}, \overrightarrow{h'}) = \overrightarrow{O}^{m}_{n'}(I_{n'}, \overrightarrow{h'}) \) for all \( n' \in N(S) \) we are looking for nodes that can – from the attacker’s perspective – produce the same trace of outputs.

The process of checking a program’s policy consistency for a bounded memory attacker is similar to that of a perfect recall attacker (Definition 12); the only difference is that we should use \( \overrightarrow{O}^{m}_{n} \) instead of \( \overrightarrow{O}^{m}_{n} \) during the generation of the formula for checking consistency.

To illustrate this, we revisit Program 13 and check its policy consistency under a bounded memory attacker with memory capacity of \( m = 2 \). For example, the generated formula for node \( n3 \) is:

\[
\left( P_{c_{n3}}(0, \{x, y\}) \land \left( \bigwedge_{n' \in N(S)} \neg (P_{c_{n'}}(0, \{x', y'\}) \land \overrightarrow{O}^{2}_{n'}(0, \{x', y'\})) \right) \right)
\]

The output sequence of node \( n3 \) is \( \overrightarrow{O}^{2}_{n3} = (1, 1) \). The formula is satisfiable if there exists a value for \( y \) or \( x \) where \( P_{c_{n3}}(y) \) holds, and for all nodes \( n \) it falsifies either the path conditions or the equality between outputs. For this attacker, it is possible for the nodes which are not on the same level to have equal outputs, so we have to consider all \( n' \in N(S) \). However, in this example, there are two nodes that can possibly produce an output sequence equal to \((1, 1), n2 \) with output sequence \((x, 1) \) and \( n3 \) with \((1, 1) \), for both of which the path condition is also true. We consider \( n3 \) first, because in this case both of the output sequences are \((1, 1) \), which means that the inner formula is true, hence the result of conjunction is false. This means that even without considering \( n2 \) we can be conclude that the whole formula is unsatisfiable and the policy change at node \( n5 \) is consistent. Similarly, we can apply Definition 16 to all of the nodes in \( S \) and show that Program 13 is in fact secure.

The following theorem shows soundness of Definition 16 wrt. the security condition for a bounded memory attacker.

**Theorem 5.** Given a SOT \( S \), if the formula in Definition 16 is unsatisfiable for all nodes \( n \in S \), then \( S \) satisfies Definition 3 for the bounded memory attacker.

**Proof.** Similar to the proof of Theorem 2.

Appendix B.
Examples for the Forgetful Attacker

In this section, we revisit some of the examples presented in Section 4 to demonstrate how a forgetful attacker’s knowledge is calculated.

For Program 5 we calculate the attacker’s knowledge after the output of line 8. Without the loss of generality, let us assume \( x = 5 \) and \( y = 7 \). At this point, the attacker has observed the trace \( t = 7.1.2 \). There is also an unobservable new policy event between 1 and 2, thus the splitPolicy(\( t \)) function gives us the sub-traces \((7.1, 2) \). The length of the sub-trace \( t_1 = 7.2 \) is 2, so the knowledge of attacker will be all of the stores that can produce a trace ending with 2.
that has exactly two other observable events (of any value) before that:
\[ k^{fr}_{8}(c, \sigma, p_{\text{Init}}, A) = \{ \sigma' \mid (c, \sigma', p_{\text{Init}}) \xrightarrow{t''} j \]
\[ \land (t''_1, t''_2) = \text{split}(t''_{\text{A}}, 2) \]
\[ \land t''_1 = 1 \}

This corresponds to all the stores with any value for \( x \), and since the active policy \( p \) at execution point \( i = 8 \) is also the set of all the stores, security condition 3 holds. If we repeat this process for all execution points, we can see that the program is accepted by Definition 3.

Similarly, the knowledge of the attacker at line 8 of Program 6 will be all of the stores that can produce a trace that ends with sub-trace 7.2 and have exactly one other observable event before that, which will be the stores with any value for \( x \), but only value 7 for \( y \). Since the active security policy at this point is the set of all stores with any value for both \( x \) and \( y \), the security condition \( p_{\text{8}} \subseteq k^{fr}_{8}(c, \sigma, p_{\text{Init}}, A) \) does not hold and Program 6 is rejected as insecure.

In Program 7, for a positive \( x \), the attacker observes the trace \( t = 1.11 \) after the output on line 8. The splitPolicy(\( t \)) function gives us the tuple \((1.1, 1)\) and since \((1.1)\) is 2, the attacker knowledge will be all of the stores that can produce a trace that ends with 1, and have exactly two other observable event before that:
\[ k^{fr}_{8}(c, \sigma, p_{\text{Init}}, A) = \{ \sigma' \mid (c, \sigma', p_{\text{Init}}) \xrightarrow{t''} j \]
\[ \land (t'_1, t'_2) = \text{split}(t'_{\text{A}}, 2) \]
\[ \land t''_1 = 1 \}

The only stores that can produce such a trace are the ones with \( x > 0 \), which implies that the security condition does not hold and the program is rejected as insecure.

### Appendix C.

**Proof of Verification Soundness**

Here we present sketches for the proofs of Theorems 2, 3, and 4.

**Theorem 2.** Given a SOT \( S \), if the formula in Definition 11 is unsatisfiable for all nodes \( n \in S \), then \( S \) satisfies Definition 3.

**Proof.** By Definition 3, a program is insecure if there is a point \( i \) during the execution in which the policy is not contained in the knowledge (i.e., \( p_i \not\subseteq k_i \)). This means that there is a value such that it is in the policy but not in the knowledge. Similarly, in the SOT, if the formula corresponding to a node \( n \) is unsatisfiable, it means that there exist two stores that satisfy the policy \( P(\overrightarrow{T}, \overrightarrow{h}) \), but either one store does not reach the output node or the two stores produce different output sequences. This implies that there is an initial store \((\overrightarrow{T}, \overrightarrow{h}) \in P(\overrightarrow{T}, \overrightarrow{h})\), such that \((\overrightarrow{T}, \overrightarrow{h}) \not\subseteq k_i \), thus violating the security condition.

On the other hand if the formula at node \( n \) is unsatisfiable, it implies that for any initial state \((\overrightarrow{T}, \overrightarrow{h})\) that satisfies the policy \( P(\overrightarrow{T}, \overrightarrow{h}) \) and reaches node \( n \) producing the output sequence \( \overrightarrow{O_n} \), it is impossible to find another state \((\overrightarrow{T}, \overrightarrow{h}')\) that satisfies the policy and reaches some output node \( n' \) (i.e., \( n \in N(S) \) and \( P_{\text{End}}(\overrightarrow{T}, \overrightarrow{h}') \)) yielding a different output sequence \( \overrightarrow{O}_{n'} \). If we repeat this process for all nodes \( n \in S \), and none of their formulas are satisfiable, it means that there are no outputs in SOT \( S \) such that \( p_i \not\subseteq k_i \).

**Theorem 3.** Given a SOT \( S \), if the formula in Definition 12 is unsatisfiable for all nodes \( n \in S \) such that \( n \) follows a policy change, then \( S \) satisfies Definition 2.

**Proof.** The proof of this theorem is similar to Theorem 2. However, because in the SOT we do not have any nodes for the policy change, we have to capture the policy changes on the next output nodes.

In the policy consistency check formula (Definition 12) the policy part of the formula \( (P(\overrightarrow{T}, \overrightarrow{h})) \) is generated at node \( n \) because we want it to reflect the new policy, however, the rest of the formula is generated for \( n \)’s parent node (i.e., \( \text{parent}(n) \)). The satisfiability of this formula means that there exist two stores that satisfy the new policy \( P(\overrightarrow{T}, \overrightarrow{h}) \) at node \( n \), but either one store does not reach an output or the two stores produce different output sequences up to \( \text{parent}(n) \). This implies that there is an initial store \((\overrightarrow{T}, \overrightarrow{h}) \in P_n(\overrightarrow{T}, \overrightarrow{h}) \), such that \((\overrightarrow{T}, \overrightarrow{h}) \not\subseteq k_{i-1} \), thus violating the policy consistency condition.

If we repeat this process for all nodes \( n \in S \) with new policy, and none of their formulas are satisfiable, it means that there are no policy changes in SOT \( S \) such that \( p_i \not\subseteq k_{i-1} \). Here we assume that there is always an output after a policy change. For programs that have a policy change as their last command, we can use the node \( \text{End} \) for policy consistency check and apply Definition 12.

**Theorem 4.** Given a SOT \( S \), if the formula in Definition 13 is unsatisfiable for all nodes \( n \in S \), then \( S \) satisfies Definition 3 for the forgetful attacker.

**Proof.** The difference between the the security condition of the forgetful attacker and the perfect recall is that the latter uses Definition 7 to calculate the attacker’s knowledge.

This definition limits the observations of the attacker to the number of outputs before the policy change and the values of outputs after a policy change. The output function \( \overrightarrow{O}^{fr}_{n} \) used in the forgetful attacker’s formula (Definition 13) captures this behavior by ignoring the value of outputs before the last policy change (replacing them with a constant value), and only keeping the actual value of the outputs that happened after the policy change.

The rest is similar to the proof of Theorem 2. The satisfiability of the formula of Definition 13 means that there exist two stores that satisfy the new policy \( P(\overrightarrow{T}, \overrightarrow{h}) \) at node \( n \), but if they reach an output, the output sequences up to node \( n \) wrt. \( \overrightarrow{O}^{fr}_{n} \) will be different. This implies that there is an initial store \((\overrightarrow{T}, \overrightarrow{h}) \in P_n(\overrightarrow{T}, \overrightarrow{h}) \), such that \((\overrightarrow{T}, \overrightarrow{h}) \not\subseteq k_{i}^{fr} \), thus violating the security condition.

### Appendix D.

**Proof of Attacker Power**

In this section, we present Theorem 6 to prove the claim that in the absence of inconsistent policy changes,
a program which is secure against a perfect recall attacker is also secure against a bounded memory attacker.

**Theorem 6.** Given a program $c$ with no inconsistent policy changes, initial store $\sigma$, and initial policy $p_{\text{init}}$, if for all execution points $i$, $c$ is secure against perfect recall attacker $A_{\text{per}}$, it is also secure against bounded memory attacker $A_{\text{bnd}}$ with memory capacity $m \in N$. Formally:

$$p_i \subseteq k_i(c,\sigma,p_{\text{init}},A_{\text{per}}) \implies p_i \subseteq k_i^{\text{bnd}}(c,\sigma,p_{\text{init}},A_{\text{bnd}}^m, m) \quad \forall m \in N$$

**Proof.** We should consider all execution points $i$ such that

$$(c,\sigma,p_{\text{init}}) \frac{\Rightarrow}{\Delta} (c_i,\sigma_i,p_i)$$

and continue with structural induction on command $c_i$.

All of the commands presented in Figure 1 should be considered here. However, not all of them have an effect on the knowledge, therefore we only investigate command $\text{output}_i(e)$. Without the loss of generality let us assume that $e$ is visible to the attacker $A_{\text{bnd}}$.

Since knowledge is monotone, the more observations an attacker has, the smaller his knowledge set will be. We can use this fact to limit the number of cases we have to investigate for different values of $m$. Thus, we only consider two scenarios:

- If $|\{(t,\epsilon)\}|_{A_{\text{bnd}}} \leq m$ then the bounded memory attacker with memory capacity $m$ is going to know everything that the perfect recall attacker knows. Hence

$$k_i(c,\sigma,p_{\text{init}},A_{\text{per}}) = k_i^{\text{bnd}}(c,\sigma,p_{\text{init}},A_{\text{bnd}}^m, m)$$

and by assumption we know that $p_i \subseteq k_i(c,\sigma,p_{\text{init}},A_{\text{per}})$, we can conclude:

$$p_i \subseteq k_i^{\text{bnd}}(c,\sigma,p_{\text{init}},A_{\text{bnd}}^m, m)$$

- If $|\{(t,\epsilon)\}|_{A_{\text{bnd}}} > m$ then the bounded memory attacker $A_{\text{bnd}}^m$ had less observations than the perfect recall attacker. Hence

$$k_i(c,\sigma,p_{\text{init}},A_{\text{per}}) \subseteq k_i^{\text{bnd}}(c,\sigma,p_{\text{init}},A_{\text{bnd}}^m, m)$$

and by assumption we know that $p_i \subseteq k_i(c,\sigma,p_{\text{init}},A_{\text{per}})$, we can conclude that

$$p_i \subseteq k_i^{\text{bnd}}(c,\sigma,p_{\text{init}},A_{\text{bnd}}^m, m)$$

also holds.

As a result, the security condition:

$$p_i \subseteq k_i^{\text{bnd}}(c,\sigma,p_{\text{init}},A_{\text{bnd}}^m, m) \quad \forall m \in N$$

holds for all values of $m \in N$.

Additionally, if $c_i$ is $\text{setPolicy}(p')$ we can use the assumption that program $c$ does not have any inconsistent policies to conclude that Definition 2 holds for perfect recall attacker $A_{\text{per}}$ for all execution points $i$. Since we already established that bounded memory attacker $A_{\text{bnd}}^m$’s knowledge is less than or equal to $A_{\text{per}}$ at each execution point, it is straightforward to show that:

$$p_i \subseteq k_{i-1}^{\text{bnd}}(c,\sigma,p_{\text{init}},A_{\text{bnd}}^m, m)$$

which means that the policy changes are also consistent for bounded memory attacker $A_{\text{bnd}}^m$.

Theorem 1 proves a similar claim for the forgetful attackers.

**Theorem 1.** Given a program $c$, initial store $\sigma$, and initial policy $p_{\text{init}}$, if for all execution points $i$, $c$ is secure against perfect recall attacker $A_{\text{per}}$, it is also secure against forgetful attacker $A_{\text{frg}}$. Formally:

$$[\sigma]^{p_i}_{A} \subseteq k_i(c,\sigma,p_{\text{init}},A_{\text{per}}) \implies [\sigma]^{p_i}_{A} \subseteq k_i^{\text{frg}}(c,\sigma,p_{\text{init}},A_{\text{frg}})$$

**Proof.** The proof of this theorem is similar to Theorem 6. We consider all execution points $i$ such that:

$$(c,\sigma,p_{\text{init}}) \frac{\Rightarrow}{\Delta} (c_i,\sigma_i,p_i)$$

and only investigate the case where command $c_i$ is $\text{output}_i(e)$, and assume that $e$ is visible to the attacker $A_{\text{frg}}$. Let us consider three scenarios:

- If $\text{splitPolicy}(t)$ is $(c,t)$, then the observations of forgetful attacker are the same as the observations of the perfect recall attacker, hence:

$$k_i(c,\sigma,p_{\text{init}},A_{\text{per}}) = k_i^{\text{frg}}(c,\sigma,p_{\text{init}},A_{\text{frg}})$$

Since by assumption we know that $p_i \subseteq k_i(c,\sigma,p_{\text{init}},A_{\text{per}})$, we can conclude:

$$p_i \subseteq k_i^{\text{frg}}(c,\sigma,p_{\text{init}},A_{\text{frg}})$$

- If $\text{splitPolicy}(t)$ is $(t,\epsilon)$, then the forgetful attacker makes no observations after the policy change and only knows $\{(t,\epsilon)\}$. Thus,

$$k_i(c,\sigma,p_{\text{init}},A_{\text{per}}) \subseteq k_i^{\text{frg}}(c,\sigma,p_{\text{init}},A_{\text{frg}})$$

Hence, we can conclude that:

$$p_i \subseteq k_i^{\text{frg}}(c,\sigma,p_{\text{init}},A_{\text{frg}})$$

- If $\text{splitPolicy}(t)$ is $(t_1,t_2)$. Since knowledge is monotone and $t_2$ is a sub-trace of $t$, the knowledge set of an observer that sees $t_2$ is bigger that the knowledge set of the observer of $t$. Additionally, for all events before $t_2$, the attacker $A_{\text{per}}$ observed the actual value of the event while the attacker $A_{\text{frg}}$ only knows that an event has occurred. Therefore, it is straightforward to show that the knowledge of $A_{\text{frg}}$ is less than the knowledge of $A_{\text{per}}$:

$$k_i(c,\sigma,p_{\text{init}},A_{\text{per}}) \subseteq k_i^{\text{frg}}(c,\sigma,p_{\text{init}},A_{\text{frg}})$$

Therefore we can conclude that:

$$p_i \subseteq k_i^{\text{frg}}(c,\sigma,p_{\text{init}},A_{\text{frg}})$$
TABLE 3: Benchmark evaluation results (Extended Table)

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<thead>
<tr>
<th>Program</th>
<th>Attacker Type</th>
<th>Inconsistent Policy Mode</th>
<th>JPF Inst</th>
<th>OA</th>
<th>ME</th>
<th>FG</th>
<th>FS</th>
<th>PR</th>
<th>SOT Nodes</th>
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</table>

**DynCoVer Results:** ✓ the program is secure; × the program is insecure; † the program has an inconsistent policy change.

Inconsistent Policy: What to do when facing an inconsistent policy: Reject the inconsistent policies; Repair the policy.

**JPF Inst:** total number of instructions executed by JPF

**Time:** OA: overall; ME: model extraction; FG: interference formula generation; FS: interference formula satisfiability checking; PR: policy repair (only if applicable)

**SOT Nodes:** Number of nodes in the generated Symbolic Output Tree