Static Specification Mining Using Automata-Based Abstractions

Sharon Shoham Eran Yahav Stephen Fink Marco Pistoia

Abstract— **We present a novel approach to client-side mining of temporal API specifications based on static analysis. Specifically, we present an interprocedural analysis over a combined domain that abstracts both aliasing and event sequences for individual objects. The analysis uses a new family of automata-based abstractions to represent unbounded event sequences, designed to disambiguate distinct usage patterns and merge similar usage patterns.**

Additionally, our approach includes an algorithm that summarizes abstract traces based on automata clusters, and effectively rules out spurious behaviors.

We show experimental results mining specifications from a number of Java clients and APIs. The results indicate that effective static analysis for client-side mining requires fairly precise treatment of aliasing and abstract event sequences. Based on the results, we conclude that static client-side specification mining shows promise as a complement or alternative to dynamic approaches.

Index Terms— **Specification Mining, Static Analysis, Typestate.**

I. Introduction

There is only one thing more painful than learning from experience and that is not learning from experience.
– Archibald MacLeish

Specifications of program behavior play a central role in many software engineering technologies. In order to apply such technologies to software lacking formal specifications, much research has addressed *mining* specifications directly from code [1], [2], [5], [29], [30], [31], [18], [10], [14], [23], [9].

Most such research addresses *dynamic analysis*, inferring specifications from observed behavior of representative program runs. Dynamic approaches enjoy the significant virtue that they learn from behavior that definitively occurs in a run. On the flip side, dynamic approaches can learn *only* from available representative runs; incomplete coverage remains a fundamental limitation.

The Internet provides access to a huge body of representative clients for many APIs, through myriad public code repositories and search engines. However, the amount of code available for inspection vastly exceeds the amount of code amenable to automated dynamic analysis. Dynamic analysis requires someone to build, deploy, and set up an appropriate environment for a program run. These tasks, difficult and time-consuming for a human, lie far beyond the reach of today's automated technologies.

To avoid the difficulties of running a program, a tool can grab code, and apply static program analysis to approximate its behavior. For this reason, static analysis may add value as a complement or alternative to dynamic analysis for specification mining.

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Static analyses for specification mining can be classified as *component-side*, *client-side*, or both. A component-side approach analyzes the implementation of an API, and uses error conditions in the library (such as throwing an exception) or user annotations to derive a specification.

In contrast, client-side approaches examine not the implementation of an API, but rather the ways client programs use that API. Thus, client-side approaches can infer specifications that represent how a particular set of clients uses a general API, rather than approximating safe behavior for all possible clients. In practice, this is a key distinction, since a specification of non-failing behaviors often drastically over-estimates the intended use cases.

This paper addresses static analysis for client-side mining, applied to API specifications for object-oriented libraries. The central challenge is to accurately track sequences that represent typical usage patterns of the API. In particular, the analysis must deal with three difficult issues:

- **Aliasing.** Objects from the target API may flow through complex heap-allocated data structures.
- **Unbounded Sequence Length.** The sequence of events for a particular object may grow to any length; the static analysis must rely on a sufficiently precise yet scalable finite abstraction of unbounded sequences.
- **Noise.** The analysis will inevitably infer some spurious usage patterns, due to either analysis imprecision or incorrect client programs. A tool must discard spurious patterns in order to output intuitive, intended specifications.

We present a two-phase approach consisting of (1) an *abstract-trace collection* to collect sets of possible behaviors in client programs, and (2) a *summarization* phase to filter out noise and spurious patterns. We also suggest refinement mechanisms to make the analysis more precise. Specifically, the main contributions of this paper are:

- a framework for client-side specification mining based on flow-sensitive, context-sensitive abstract interpretation over a combined domain abstracting both aliasing and event sequences,
- a novel family of abstractions to represent unbounded event sequences,
- novel algorithms to summarize abstract traces based on automata clusters,
- refinement that uses inspection of selected mined traces to make the framework more precise, and
- results from a prototype implementation that mines several interesting specifications from non-trivial Java programs.

The experimental results indicate that in order to produce reasonable specifications, the static analysis must employ sufficiently precise abstractions of aliases and event sequences. Based on experience with the prototype implementation, we discuss strengths

```
class SocketChannelClient {
 void example() {
  Collection<SocketChannel> channels = createChannels();
  for (SocketChannel sc : channels) {
   sc.connect(new InetSocketAddress("tinyurl.com/23qct8",80));
   while (!sc.finishConnect()) {
    // ... wait for connection ...
   }
   if (?) {
    receive(sc);
   } else {
    send(sc);
   }
  }
  closeAll(channels);
 }
 void closeAll(Collection<SocketChannel> chnls) {
   for (SocketChannel sc : chnls) { sc.close(); }
 }
 Collection<SocketChannel> createChannels() {
  List<SocketChannel> list = new LinkedList<SocketChannel>();
  list.add(createChannel("http://tinyurl.com/23qct8", 80));
  list.add(createChannel("http://tinyurl.com/23qct8", 80));
  //...
  return list;
 }
 SocketChannel createChannel(String hostName, int port) {
  SocketChannel sc = SocketChannel.open();
  sc.configureBlocking(false);
  return sc;
 }
 void receive(SocketChannel x) {
  File f = new File("ReceivedData");
  FileOutputStream fos = new FileOutputStream(f,true);
  ByteBuffer dst = ByteBuffer.allocateDirect(1024);
  int numBytesRead = 0;
  while (numBytesRead >= 0) {
   numBytesRead = x.read(dst);
   fos.write(dst.array());
  }
  fos.close();
 }
 void send(SocketChannel x) {
  for (?) {
   ByteBuffer buf = ByteBuffer.allocateDirect(1024);
   buf.put((byte) 0xFF);
   buf.flip();
   int numBytesWritten = x.write(buf);
  }
 }
}
```

Fig. 1. A simple program using APIs of interest.

and weaknesses of static analysis for specification mining. We conclude that this approach shows promise as a path to more effective specification mining tools.

II. Overview

Fig. 1 shows a simple Java program that uses `SocketChannel` objects. Our goal is to infer the pattern of `SocketChannel` API calls the program invokes on any individual object. Fig. 2 shows a partial specification of the `SocketChannel` API,[1] representing a desirable analysis output. The specification indicates that the program must *connect* a `SocketChannel` before using it. Connecting a channel entails a sequence of three operations: (1) configuring the channel's blocking mode, (2) requesting a connection, and (3) finishing the connection process by waiting for the connection to be established. Once the channel is connected, the program can invoke `read` and `write` in any order, and eventually, `close`.

To extract this pattern from the example code, an analysis must deal with complex heap-allocated data structures in order

[1]Figures in the paper use abbreviated method names.

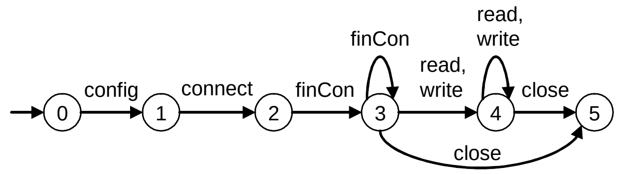


Fig. 2. Partial specification for `SocketChannel`.

to track the state of individual objects. Note that the method `createChannels` returns a collection containing an arbitrary number of dynamically allocated `SocketChannel` objects, which flow across procedure boundaries to other API calls. In order to make sense of the temporal sequence of operations on any individual channel, the analysis must employ precise alias analysis to track the sequence of operations on individual objects.

In addition to challenges with alias analysis, the specification inference must deal with a second difficult abstraction issue: tracking state related to a potentially *unbounded* sequence of events for each object. For example, the `receive` method of Fig. 1 invokes `x.read(dst)` in a `while` loop with unknown bounds.

A. Our Approach

Our approach consists of two phases: an *abstract-trace collection* phase, which accumulates abstractions of event sequences for abstract objects, using *abstract histories*, and a *summarization* phase, which consolidates the abstract histories and reduces noise. We also suggest *refinement* mechanisms to make the analysis more precise.

1) Abstract-Trace Collection: We statically collect data regarding the event sequences for objects of a particular type. We use abstract interpretation [6], where an abstract value combines pointer information with an *abstract history*, a bounded representation of the sequence of events for a tracked object in the form of an automaton.

Our trace collection analysis is governed by two general parameters: (i) the heap abstraction and (ii) the history abstraction. Table I shows the abstract histories generated for the example program, varying the choice of heap abstraction and history abstraction.

The table columns represent two heap abstractions presented previously [11]; the *Base* abstraction, which relies on a flow-insensitive Andersen's pointer analysis [3], and the *APFocus* abstraction, which employs fairly precise flow-sensitive access-paths analysis. The table rows represent variations on the history abstraction. The history abstraction relies on an *extend* operator and a *merge* operator. In the table, we fix the extend operator to one that distinguishes past behavior (the *Past* relation of Section IV-B.3), and vary the choice of merge operator.

The merge operator controls the *join* used to combine histories that arise at the same program point but in different execution paths. The *Total* operator joins *all* histories that occur in a particular abstract program state. The *Exterior* operator joins only histories that share a common recent past, as will be described formally later.

In the table, specifications become less permissive (and more precise) as one moves right and/or down. That is, the combination Base/Past/Total is the most permissive, and APFocus/Past/Exterior is the least permissive. The results show that the analysis requires

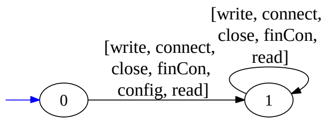
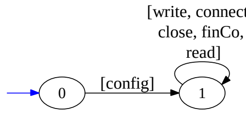
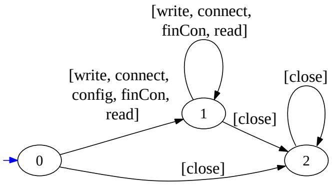
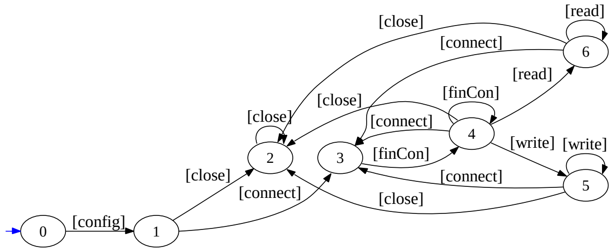
	Base	APFocus
Past/ Total		
Past/ Exterior		

TABLE I

RESULTS OF MINING THE RUNNING EXAMPLE WITH VARYING HEAP ABSTRACTIONS AND MERGE ALGORITHMS.

both a rather precise aliasing and a rather precise merge operator in order to approach the desired result.

2) Summarization: Abstract trace collection generates a set of abstract histories that overapproximates possible client behavior. However, some generated histories will admit spurious behavior (noise), either due to analysis imprecision or bugs in the client corpus.

The summarization phase employs statistical approaches to consolidate the collected abstract histories. In contrast to most previous work, which summarizes either raw event traces [5], [2] or event pairs [31], [29], our "raw data" (automata) already exhibit some structure resembling a candidate specification.

Our summarization phase exploits this structure to perform effective noise elimination and consolidation. In particular, we show a clustering algorithm to partition the abstract histories into groups that represent related scenarios. The approach eliminates noise from each cluster independently, allowing it to distinguish noise from interference between independent use cases.

Returning to the running example, we note that the least permissive abstract history (APFocus/Past/Exterior) contains a few edges that look spurious, such as repeated calls to `close` (state 2 self-loop) and repeated calls to `connect` (state 6 to state 3). In fact, these transitions will occur in the example program if the same `SocketChannel` appears twice in the collection; however, most likely the programmer does not intend for this to happen, and perhaps some invariant rules out this pathological case. When this abstract history is summarized with others that do not exhibit this particular pathology, the summarization algorithm will rule out the spurious edges, resulting in the specification of Fig. 2.

We further note that the quality of the input abstract histories limits the quality of the summarization output. It is hard to imagine any summarization algorithm producing the desired specification based on overly permissive input, such as the abstract history from Base/Past/Total.

3) Refining Mining Results via Inspection: Even after the summarization phase, the mined specification might exhibit spurious behavior. In particular, spurious behavior which is included in the mined specification due to the history abstraction sometimes eludes the statistical summarization approaches since it repeats in many of the histories.

To deal with this source of imprecision, we propose several approaches for refining the history abstraction. We can recover some of the precision lost due to merging histories by performing "inspection" of paths in the mined specifications that are ranked as *unlikely*. *Inspection* checks the absence of a specific sequence in the training-set. We distinguish between static and dynamic inspection, and between client-side and component-side inspection. We explain how inspection may be used to dismiss some paths when it is shown that they cannot occur in any execution of the code base.

III. PRELIMINARIES

In this section, we provide some basic definitions that we will use in the rest of the paper.

Definition 3.1: Given a finite set Σ of *input symbols*, a *finite automaton* over *alphabet* Σ is a tuple $\mathcal{A} = (\Sigma, \mathcal{Q}, init, \delta, \mathcal{F})$, where $\mathcal{Q}$ is a finite set of *states*, $init \in \mathcal{Q}$ is the *initial state*, $\delta\colon \mathcal{Q}\times\Sigma \to 2^{\mathcal{Q}}$ is the *transition function* and $\mathcal{F} \subseteq \mathcal{Q}$ is the set of *accepting states*.

An automaton $\mathcal{A}$ is *deterministic* if for every $q \in \mathcal{Q}$ and $\sigma \in \Sigma$, $|\delta(q,\sigma)| \leq 1$. δ is extended to finite words in the usual way. The *language* of $\mathcal{A}$, denoted $\mathcal{L}(\mathcal{A})$, is the set of all words $\alpha \in \Sigma^*$ such that $\delta(init, \alpha) \cap \mathcal{F} \neq \emptyset$.

For an automaton state $q \in \mathcal{Q}$, we define $in_k(q) = \{\alpha \in \Sigma^k \mid \exists q' \in \mathcal{Q} : q \in \delta(q', \alpha)\}$. Similarly, $out_k(q) = \{\alpha \in \Sigma^k \mid \exists q' \in \mathcal{Q} : q' \in \delta(q, \alpha)\}$. In particular, for every $q \in \mathcal{Q}$, $in_0(q) = out_0(q) = \{\epsilon\}$, where ϵ denotes the empty sequence. To ensure that for every $q \in \mathcal{Q}$ and every $k \geq 1$, $in_k(q), out_k(q) \neq \emptyset$, we extend Σ by some $\perp \notin \Sigma$ and view each state that has no predecessor (resp. successor) as having an infinite ingoing (resp. outgoing) sequence $\perp^\omega$.

Definition 3.2 (Quotient): Let $\mathcal{A} = (\Sigma, \mathcal{Q}, init, \delta, \mathcal{F})$ be an automaton, and $\mathcal{R} \subseteq \mathcal{Q} \times \mathcal{Q}$ an equivalence relation on $\mathcal{Q}$, where $[q]$ denotes the equivalence class of $q \in \mathcal{Q}$. Then the *quotient automaton* is $Quo_{\mathcal{R}}(\mathcal{A}) = (\Sigma, \{[q] \mid q \in \mathcal{Q}\}, [init], \delta', \{[q] \mid q \in \mathcal{F}\})$, where $\delta'([q], \sigma) = \{[q'] \mid \exists q'' \in [q] : q' \in \delta(q'', \sigma)\}$.

The quotient automaton is an automaton whose states consist of the equivalence classes of states of the original automaton. The outgoing transitions are then defined as the union of the outgoing transitions of all the states in the equivalence class (this might result in nondeterministic automata even if $\mathcal{A}$ is deterministic). It is easy to show that $\mathcal{L}(\mathcal{A}) \subseteq \mathcal{L}(Quo_{\mathcal{R}}(\mathcal{A}))$.

In the following, the alphabet Σ consists of method calls (observable events) over the objects of the tracked type.

IV. Abstract Trace Collection

Our trace collection analysis produces "abstract histories", which summarize the event sequences of many possible concrete executions. The analysis propagates a sound approximation of program state that tracks alias information and histories for each abstract object.

In the following, we describe the analysis in terms of a sound abstraction of an instrumented concrete semantics.

Statement	**Concrete History**
sc = open()	$\rightarrow\odot$
sc.config	$\rightarrow\circ\xrightarrow{\text{cfg}}\odot$
sc.connect	$\rightarrow\circ\xrightarrow{\text{cfg}}\circ\xrightarrow{\text{cnc}}\odot$
sc.finCon	$\rightarrow\circ\xrightarrow{\text{cfg}}\circ\xrightarrow{\text{cnc}}\circ\xrightarrow{\text{fin}}\odot$
...	
sc.finCon	$\rightarrow\circ\xrightarrow{\text{cfg}}\circ\xrightarrow{\text{cnc}}\circ\xrightarrow{\text{fin}}\ldots\xrightarrow{\text{fin}}\odot$
x.read	$\rightarrow\circ\xrightarrow{\text{cfg}}\circ\xrightarrow{\text{cnc}}\circ\xrightarrow{\text{fin}}\ldots\xrightarrow{\text{fin}}\circ\xrightarrow{\text{rd}}\odot$
...	
x.read	$\rightarrow\circ\xrightarrow{\text{cfg}}\circ\xrightarrow{\text{cnc}}\circ\xrightarrow{\text{fin}}\ldots\xrightarrow{\text{fin}}\circ\xrightarrow{\text{rd}}\ldots\xrightarrow{\text{rd}}\odot$
sc.close	$\rightarrow\circ\xrightarrow{\text{cfg}}\circ\xrightarrow{\text{cnc}}\circ\xrightarrow{\text{fin}}\ldots\xrightarrow{\text{fin}}\circ\xrightarrow{\text{rd}}\ldots\xrightarrow{\text{rd}}\circ\xrightarrow{\text{cl}}\odot$

Fig. 3. Example of concrete histories for an object of type SocketChannel in the example program.

A. Concrete Instrumented Semantics

We define an instrumented concrete semantics that tracks the concrete trace of events for each concrete object. We refer to the concrete trace of events as the *concrete history* of the concrete object. We start with a standard concrete semantics for an imperative object-oriented language, defining a program state and evaluation of an expression in a program state.

Restricting our attention to reference types, the semantic domains are defined in a standard way as follows:

$$\begin{array}{lll}
L^\natural & \in & 2^{objects^\natural} \\
v^\natural & \in & Val = objects^\natural \cup \{null\} \\
\rho^\natural & \in & Env = VarId \to Val \\
\pi^\natural & \in & Heap = objects^\natural \times FieldId \to Val \\
state^\natural = \langle L^\natural, \rho^\natural, \pi^\natural \rangle & \in & States = 2^{objects^\natural} \times Env \times Heap
\end{array}$$

where $objects^\natural$ is an unbounded set of dynamically allocated objects, *VarId* is a set of local variable identifiers, and *FieldId* is a set of field identifiers.

A *program state* keeps track of the set $L^\natural$ of allocated objects, an *environment* $\rho^\natural$ mapping local variables to values, and a mapping $\pi^\natural$ from fields of allocated objects to values.

In our instrumented semantics, each concrete object is mapped to a "concrete history" that records the sequence of events that has occurred for that object. Technically, we define the notion of a *history* which captures a regular language of event sequences.

Definition 4.1: A *history* h is a finite automaton $(\Sigma, \mathcal{Q}, init, \delta, \mathcal{F})$, where $\mathcal{F} \neq \emptyset$. $\mathcal{F}$ is also called the set of *current states*. We define the *traces represented by* h, $Tr(h)$, to be the language $\mathcal{L}(h)$.

A *concrete history* $h^\natural$ is a special case of a history that encodes a single finite trace of events, that is, where $Tr(h^\natural)$ consists of a single finite trace of events. In Sec. IV-B we will use the general notion of a history to describe a regular language of event sequences. We refer to a history that possibly describes more than a single trace of events as an *abstract history*.

Example 4.2: Fig. 3 shows examples of concrete histories occurring for a `SocketChannel` object of the example program at various points of the program. Fig. 4 and Fig. 5 show examples of abstract histories describing regular languages of events. In all figures, current states are depicted as double circles. Note that the automaton corresponding to an abstract history may be nondeterministic (e.g., as shown in Fig. 5).

We denote the set of all concrete histories by $\mathcal{H}^\natural$. We augment every concrete state $\langle L^\natural, \rho^\natural, \pi^\natural \rangle$ with an additional mapping $his^\natural \colon L^\natural \rightharpoonup \mathcal{H}^\natural$ that maps an allocated object of the tracked type to its concrete history. A state of the instrumented concrete semantics is therefore a tuple $\langle L^\natural, \rho^\natural, \pi^\natural, his^\natural \rangle$.

Given a state $\langle L^\natural, \rho^\natural, \pi^\natural, his^\natural \rangle$, the semantics generates a new state $\langle L^{\natural\prime}, \rho^{\natural\prime}, \pi^{\natural\prime}, his^{\natural\prime} \rangle$ when evaluating each statement. We assume a standard interpretation for program statements updating $L^\natural$, $\rho^\natural$, and $\pi^\natural$. The $his^\natural$ component changes when encountering object allocations and observable events:

- *Object Allocation:* For a statement `x = new T()` allocating an object of the tracked type, a new (fresh) object $l_{new} \in objects^\natural \setminus L^\natural$ is allocated, and $his^{\natural\prime}(l_{new}) = h_0^\natural$, where $h_0^\natural = (\Sigma, \{init\}, init, \delta_0, \{init\})$ and δ_0 is a transition function that maps every state and event to an empty set. That is, the newly allocated object is mapped into the empty-sequence history.
- *Observable Events:* For a statement `x.m()` where $\rho^\natural(x)$ is of the tracked type T, the object $\rho^\natural(x)$ is mapped to a new concrete history $extend^\natural(h^\natural, m)$, where $h^\natural = his^\natural(\rho^\natural(x))$ and $extend^\natural : \mathcal{H}^\natural \times \Sigma \to \mathcal{H}^\natural$ is the concrete *extend transformer* that adds exactly one new state to $h^\natural$, in the natural way, to reflect the call to $m()$.

Fig. 3 shows the evolution of concrete histories for an object in the example program. Each concrete history records the sequence of observable events (method calls) upon the `SocketChannel` during a particular execution. Note that the length of a concrete history is a priori unknown, as events may occur in loops.

B. Abstract Semantics

The instrumented concrete semantics uses an unbounded description of the program state, resulting from a potentially unbounded number of objects, each with a potentially unbounded history. In this section we describe an abstract semantics that conservatively represents the instrumented semantics with various degrees of precision and cost.

1) Abstract States: Following [11], we base the abstraction on a global *heap graph*, obtained through a flow-insensitive, partially context-sensitive subset-based may points-to analysis [3]. This provides a partition of the *objects*$^\natural$ set into abstract objects, each partition with a unique name called an *instance key*.

The heap graph representation of our motivating example contains a single instance key for type `SocketChannel`, representing all the objects allocated in `createChannel`.

An abstract program state consists of a set of tuples, called "factoids." Each factoid represents an abstract object (instance key) within the abstract program state. It summarizes the heap properties of the abstract object, as well as its history. More precisely, a factoid is a tuple $\langle o, \textit{heap-data}, h\rangle$, where

- o is an instance key.
- *heap-data* consists of multiple components describing heap properties of o (described below).
- h is the abstract history representing the traces observed for o until the corresponding execution point.

An abstract state can contain multiple factoids for the same instance key o, representing different alias contexts and abstract histories.

The *heap-data* component of the factoid is crucial for precision; we adopt the *heap-data* abstractions of [11]. Intuitively, the heap abstraction relies on the combination of a preliminary scalable (e.g. flow-insensitive) pointer analysis and selective predicates indicating access-path aliasing, and information on object uniqueness. Technically, the *heap-data* component of the factoid uses tuples of the form $\langle \textit{unique}, \textit{AP}_{\textit{must}}, \textit{May}, \textit{AP}_{\textit{mustNot}}\rangle$ where:

- *unique* indicates whether the corresponding instance key has a single concrete live object.
- $\textit{AP}_{\textit{must}}$ is a set of access paths that must point-to o.
- *May* is true indicates that there are additional access paths (not in the $\textit{AP}_{\textit{must}}$ set) that may point to o.
- $\textit{AP}_{\textit{mustNot}}$ is a set of access paths that do not point-to o.

For example, a factoid with instance key o, and with $\textit{heap-data} = \langle \textit{unique} = true, \textit{AP}_{\textit{must}} = \{x.f\}, \textit{AP}_{\textit{mustNot}} = \{y.g\}, \textit{May} = true\rangle$ represents a program state in which there exists exactly one object named o, such that $x.f$ must evaluate to point to o, $y.g$ must *not* evaluate to point to o, and there *may* be other pointers to o not represented by the must access path $x.f$ (nor by the must-not access path $y.g$).

We observe that a conservative representation of the concrete program state must obey the following properties:

(a) An instance key can be indicated as unique if it represents a single object for this program state.
(b) The access path sets (the must and the must-not) do not need to be complete. This does not compromise the soundness of the analysis due to the indication of the existence of other possible aliases (the *May* indication).
(c) The instance keys induce a static heap partition based on the syntactic program location in which an object has been allocated. The must and must-not access path sets refine this partition by separating objects that are known to be must-pointed (and must-not-pointed) by specific access-paths. If the must point-to set is non-empty, the must-pointed partition represents a single concrete object.
(d) If $\textit{May} = false$, the must access path is complete; it contains all access paths to this object.

The *Base* abstraction does not make use of the *heap-data* components, meaning that $\textit{AP}_{\textit{must}} = \textit{AP}_{\textit{mustNot}} = \emptyset$, $\textit{unique} = false$ and $\textit{May} = true$ in all factoids. The *APFocus* abstraction, on the other hand, uses these components to obtain better precision. Crucially, the tracking of *must point-to* information, as well as *uniqueness*, allows *strong updates* [4] when propagating dataflow information through a statement. For more details on the heap abstraction we refer the reader to [11].

While a concrete history describes a unique trace, an abstract history typically encodes multiple traces as the language of the automaton. Different abstractions consider different history automata (e.g. deterministic vs. non-deterministic) and different restrictions on the current states (e.g. exactly one current state vs. multiple current states). We denote the set of abstract histories by $\mathcal{H}$. The remainder of this section considers semantics and variations of history abstractions.

2) Abstract Semantics: An abstract semantics for the history is defined via the following:

- An abstraction for the empty-sequence history, denoted h_0.
- An abstract extend transformer, $extend : \mathcal{H} \times \Sigma \to \mathcal{H}$, and
- A merge operator $\bigsqcup : 2^{\mathcal{H}} \to 2^{\mathcal{H}}$ which generates a new set of abstract histories that overapproximates the input set.

In the abstract semantics, the abstract history component for a fresh object is initialized to h_0. When an observable event occurs, the semantics updates the relevant histories using the $extend$ operator.

As long as the domain of abstract histories is bounded, the abstract analysis is guaranteed to terminate. However, in practice, it can easily suffer from an exponential blowup due to branching control flow. The merge operator will mitigate this blowup, accelerating convergence. Specifically, at control flow join points, all factoids that represent the same instance key and have identical heap-data are merged. Such factoids differ only in their abstract histories, i.e., they represent different execution paths of the same abstract object in the same aliasing context.

Soundness: We design the abstraction to keep track of (at least) all the traces, or concrete histories, produced by the code base. We denote the set of all concrete histories possibly generated by a code base C by $\mathcal{H}^\natural_C$. Similarly, we denote the set of all abstract histories generated by the analysis of C by $\mathcal{H}_C$. The analysis is *sound* if for every concrete history $h^\natural$ in $\mathcal{H}^\natural_C$ there exists some abstract history in $\mathcal{H}_C$ whose set of traces includes the single concrete trace represented by $h^\natural$. I.e.,

$$\bigcup_{h^\natural \in \mathcal{H}^\natural_C} Tr(h^\natural) \subseteq \bigcup_{h \in \mathcal{H}_C} Tr(h).$$

Soundness is achieved by making sure that every reachable (instrumented) concrete state *istate*$^\natural$ is represented by some reachable abstract state *istate*, meaning that for every object $o^\natural \in L^\natural$ there exists a factoid $\langle o, \textit{heap-data}, h\rangle$ in *istate* that provides a sound representation of $o^\natural$. This is a factoid whose *heap-data* component fulfills the conditions described in [11], and in addition h is a sound representation of $his^\natural(o^\natural)$, i.e. $Tr(his^\natural(o^\natural)) \subseteq Tr(h)$. Soundness of h_0, the extend transformer and of the merge operator ensure that the analysis is sound.

Definition 4.3: An abstract extend transformer $extend$ is *sound*, if whenever $Tr(h^\natural) \subseteq Tr(h)$ then for every $\sigma \in \Sigma$, $Tr(extend^\natural(h^\natural, \sigma)) \subseteq Tr(extend(h, \sigma))$.

Definition 4.4: A merge operator $\bigsqcup$ is *sound*, if for every set of abstract histories $H \subseteq \mathcal{H}$, $\bigcup_{h \in H} Tr(h) \subseteq \bigcup_{h \in \bigsqcup H} Tr(h)$.

Precision: The analysis is *precise* if it does not introduce additional behaviors that do not appear in the code base, i.e.

$$\bigcup_{h^\natural \in \mathcal{H}^\natural_C} Tr(h^\natural) = \bigcup_{h \in \mathcal{H}_C} Tr(h).$$

Remark. In practice, instead of considering the traces represented by *all* the abstract histories generated by the analysis, we consider the *prefix-closures* of the history automata at the exit-points of the program, obtained by setting $\mathcal{F}' = \mathcal{Q}$ (i.e., all the states are considered accepting). The set of observed traces is maintained when we restrict ourselves to the prefix-closures of these automata since all other traces are prefixes of the traces represented by them.

3) History Abstractions: We present a parameterized framework for history abstractions, based on intuition regarding the structure of API specifications.

Quotient-Based Abstractions: In practice, automata that characterize API specifications are often simple, and further admit simple characterizations of their states (e.g. their ingoing or outgoing sequences). Exploiting this intuition, we introduce abstractions based on quotient structures of the history automata, which provide a general, simple, and in many cases precise, framework to reason about abstract histories.

Informally, given an equivalence relation $\mathcal{R}$ and some *merge criterion*, the quotient-based abstraction generalizes histories based on their quotient structures w.r.t. $\mathcal{R}$. The merge criterion is used to determine which abstract histories are merged by the merge operator. More precisely, we define the quotient-based abstraction of $\mathcal{R}$ as follows.

- The abstraction h_0 of the empty-sequence history is $Quo_{\mathcal{R}}(h^\natural_0) = h_0$, i.e. the empty-sequence history.
- The *extend transformer* appends the new event σ to the current states, and constructs the quotient of the result. More formally, let $h = (\Sigma, \mathcal{Q}, \mathit{init}, \delta, \mathcal{F})$. For every $q_i \in \mathcal{F}$ we introduce a fresh state, $n_i \notin \mathcal{Q}$. Then $extend(h, \sigma) = Quo_{\mathcal{R}}(h')$, where $h' = (\Sigma, \mathcal{Q} \cup \{n_i \mid q_i \in \mathcal{F}\}, \mathit{init}, \delta', \{n_i \mid q_i \in \mathcal{F}\})$ with $\delta'(q_i, \sigma) = \delta(q_i, \sigma) \cup \{n_i\}$ for every $q_i \in \mathcal{F}$, and $\delta'(q', \sigma') = \delta(q', \sigma')$ for every $q' \in \mathcal{Q}$ and $\sigma' \in \Sigma$ such that $q' \notin \mathcal{F}$ or $\sigma' \neq \sigma$. Moreover, $\delta'(n_i, \sigma) = \emptyset$ for every new state n_i and for every $\sigma \in \Sigma$.
- The *merge operator* first partitions the set of histories based on the given *merge criterion*. Next, the merge operator constructs the union of the automata in each partition, and returns the quotient of the result.

It can be shown that for every equivalence relation $\mathcal{R}$ and merge criterion, the quotient-based abstraction w.r.t. $\mathcal{R}$ is sound.

To instantiate a quotient-based abstraction, we next consider options for the requisite equivalence relation and merge criteria.

Past-Future Abstractions: In many cases, API usages have the property that certain sequences of events are always preceded or followed by the same behaviors. For example, a `connect` event of `SocketChannel` is always followed by a `finishConnect` event. This means that the states of the corresponding automata are characterized by their ingoing and/or outgoing behaviors. As such, we consider quotient abstractions w.r.t. the following parametric equivalence relation.

Definition 4.5 (Past-Future Relation): Let q_1, q_2 be history states, and $k_1, k_2 \in \mathbb{N}$. We write $(q_1, q_2) \in R[k_1, k_2]$ iff $in_{k_1}(q_1); out_{k_2}(q_1) \cap in_{k_1}(q_2); out_{k_2}(q_2) \neq \emptyset$, i.e. q_1 and q_2 share both an ingoing sequence of length k_1 and an outgoing sequence of length k_2.

For example, consider the abstract history depicted in Fig. 6(a). States 2 and 4 (marked by arrows) are equivalent w.r.t. $R[1,0]$ since $in_1(2) = in_1(4) = \{\texttt{cnc}\}$ and $out_0(2) = out_0(4) = \{\epsilon\}$.

We will hereafter focus attention on the two extreme cases of the past-future abstraction, where either k_1 or k_2 is zero. Recall that $in_0(q) = out_0(q) = \{\epsilon\}$ for every state q. As a result, $R[k, 0]$ collapses to a relation that considers ingoing sequences of length k. We refer to it as $\mathcal{R}^k_{past}$, and to the abstraction as the *k-past abstraction*. Similarly, $R[0, k]$ refers to outgoing sequences of length k, in which case we also refer to it as $\mathcal{R}^k_{future}$. We refer to the corresponding abstraction as the *k-future abstraction*. Intuitively, analysis using the k-past abstraction will distinguish patterns based only on their recent past behavior, and the k-future abstraction will distinguish patterns based only on their near future behavior. These abstractions will be effective if the recent past (near future) suffices to identify a particular behavioral sequence.

Merge Criteria: Having defined equivalence relations, we now consider merge criteria to define quotient-based abstractions. A merge criterion will determine when the analysis should collapse abstract program states, thus potentially losing precision, but accelerating convergence.

We consider the following merge schemes.

- *None:* each history comprises a singleton set in the partition. This scheme is most precise, but is impractical, as it results in an exponential blowup.
- *Total:* all histories are merged into one.
- *Exterior:* the histories are partitioned into subsets in which all the histories have compatible initial states and compatible current states. Namely, histories h_1 and h_2 are merged only if (a) $(\mathit{init}_1, \mathit{init}_2) \in \mathcal{R}$; and (b) for every $q_1 \in \mathcal{F}_1$ there exists $q_2 \in \mathcal{F}_2$ s.t. $(q_1, q_2) \in \mathcal{R}$, and vice versa.

Intuitively, the total criterion forces the analysis to track exactly one abstract history for each "context" (i.e. alias context, instance key, and program point).

The exterior criterion provides a less aggressive alternative, based on the intuition that the distinguishing features of a history can be encapsulated by the features of its initial and current states, which we refer to as the "exterior" of the history. The thinking follows that if histories states differ only on the characterization of intermediate (inner) states, merging them may be an attractive option to accelerate convergence without undue precision loss.

Example: Fig. 4 presents abstract histories produced during the analysis of the single instance key in our running example, using the 1-past abstraction with exterior merge. The first row describes the histories observed at the end of the first iteration of the `for` loop of `example()`, in which a channel is connected, and either the `receive` procedure, reading bytes from the channel, or the `send` procedure, writing bytes on the channel, is invoked. These all hold abstract histories for the same instance key at the same abstract state. Each history tracks a possible execution path of the abstract object.

Although these histories refer to the same instance key and alias context, exterior merge does not apply since their current states are not equivalent. The second row shows the result of applying the extend transformer on each history after observing a `connect` event at the beginning of the next iteration of the `for` loop. The intermediate step, before the quotient construction, for

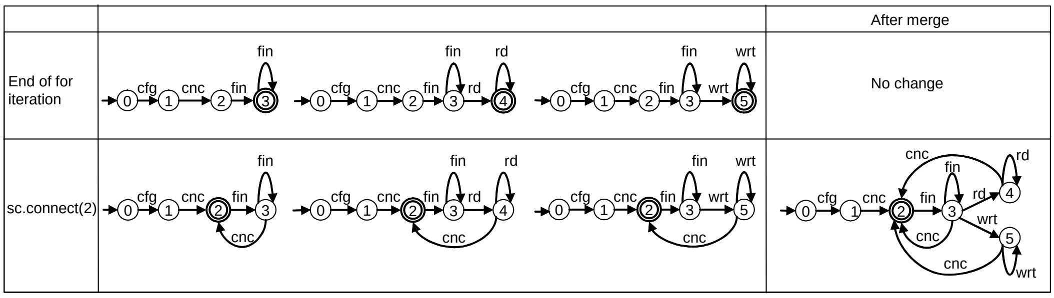


Fig. 4. Abstract interpretation with past abstraction (Exterior merge).

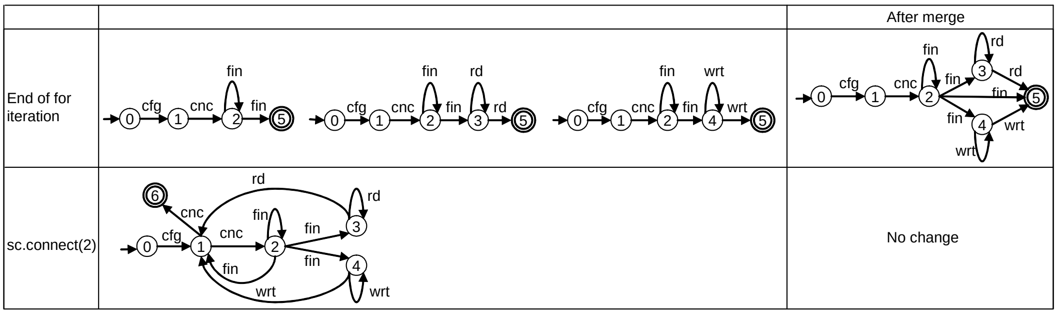


Fig. 5. Abstract interpretation with future abstraction (Exterior merge).

the automaton on the left is depicted in Fig. 6(a). There, and in all other cases as well, the new state is equivalent to an existing state according to the 1-past relation; a state with `connect` as its incoming event already exists in each automaton. As a result, extend simply adds the new transitions and adds no new states.

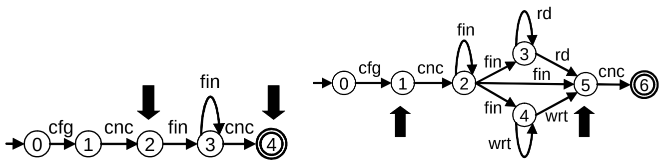
After observing this event, the resulting three histories meet the exterior merge criterion, and are therefore combined. The analysis discards the original histories and proceeds with the merged one which overapproximates them.

Fig. 5 presents the corresponding abstract histories using the 1-future abstraction with exterior merge (in fact, in this case total merge behaves identically). Unlike the case under the past abstraction, merge applies at the end of the first loop iteration, since the initial and current states are equivalent under the 1-future relation. As a result, the analysis continues with the single merged history. The second row shows the result of applying the extend transformer on it after observing a `connect` event.

Fig. 6(b) presents the intermediate step in which the merged abstract history is extended by `connect`, before the quotient is constructed. An outgoing transition labelled `connect` is added from state 5 (the previous current state) to a new state, making state 5 share a future with state 1. Thus states 1 and 5 are merged, resulting in the abstract history depicted in the second row of Fig. 5.

Nondeterminism: It is easy to verify that the quotient structure of a deterministic automaton w.r.t. $\mathcal{R}^k_{past}$ is deterministic. This ensures that the k-past abstraction always produces deterministic automata, as demonstrated by Fig. 4. On the other hand, when the future parameter is nontrivial (i.e. $k_2 \neq 0$), nondeterminism can result during the quotient construction. For example, note that in Figure 5, all the automata are non-deterministic.

Precision: If automata satisfy the following structural property, then we can prove that the past-future abstraction is fully precise:



(a) (b)

Fig. 6. (a) Past abstraction step; and (b) Future abstraction step, before quotient construction.

Definition 4.6: An automaton $\mathcal{A}$ has the (k_1, k_2)*-past-future property* if for every $q_1 \neq q_2 \in \mathcal{Q}$, $in_{k_1}(q_1); out_{k_2}(q_1) \cap in_{k_1}(q_2); out_{k_2}(q_2) = \emptyset$. This implies that every sequence of length $k_1 + k_2$ is linked to a unique automaton state.

Proposition 4.7 (Precision Guarantee): If $\bigcup_{h^\natural \in \mathcal{H}^\natural_C} Tr(h^\natural)$ is accepted by some automaton that has the (k_1, k_2)-past-future property, then the (k_1, k_2)-past-future abstraction with exterior merge is precise.

When the precision precondition is not met, different choices of k_1, k_2 in the past-future abstraction can lead to different results:

Example 4.8: The first row of Fig. 7 presents two histories produced while using the 1-past abstraction to track an abstract object that uses the `Signature` API. The history on the left uses the `verify` feature of the API, while the history on the right uses `sign`. The current states of these two histories, states 2 and 2′, are compatible ($in_1(2) = in_1(2') = \{\texttt{update}\}$), and the histories are therefore merged into the history presented in Fig. 7 on the right. In particular, states 2 and 2′ are merged. As a result, the relation between an invocation of `initVerify` (resp. `initSign`) and a later invocation of `verify` (resp. `sign`) is lost.

When using the 1-future abstraction, on the other hand, the corresponding abstract histories, depicted in the second row of Fig. 7, are not compatible since their initial states are not compatible

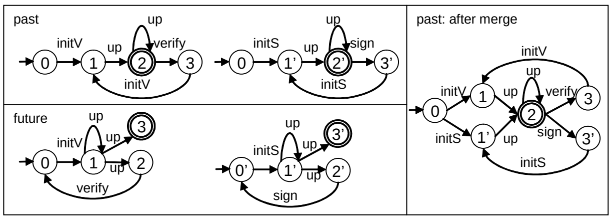


Fig. 7. Past abstraction vs. future abstraction.

($out_1(0) = \{\texttt{initVerify}\}$, while $out_1(0') = \{\texttt{initSign}\}$), and are therefore not merged, preventing the precision loss.

Of course, increasing the parameters k_1 and k_2 makes the abstraction more precise, but may negatively impact convergence.

V. Summarization using Statistical Approaches

The abstract trace collection produces automata that over-approximate the actual behavior. However, the trace collection output may represent spurious behavior due to at least three sources of noise:

- **Analysis Imprecision:** The output of the abstract interpretation is an over-approximation that may include behavior from infeasible paths.
- **Bugs in Training Corpus:** Programs in the training corpus may contain a (hopefully small) number of incorrect usages.
- **Unrestricted Methods:** Some API methods (e.g. side-effect free methods) may not play a role in the intended API specification, but may still appear in the collected abstract traces.

To deal with unrestricted methods, one could leverage *component-side* techniques to analyze the API implementation, identify side-effect-free methods, and exclude them from consideration [26]. Similarly, we could apply component-side analysis to exclude spurious patterns which lead to violations of simple safety or liveness properties. We elide further discussion of such techniques as they fall outside the scope of this paper, which focuses on client-side techniques.

To deal with the other sources of noise, we turn to statistical techniques inspired by approaches such as z-ranking [9] and the ranking of [29]. Statistical techniques distinguish signal from noise according to sample frequency. A crucial factor concerns what relative weight to assign to each sample.

We observe that each static occurrence of a usage pattern represents some thought and work by a programmer, while each dynamic occurrence typically represents an iteration of a loop counter. We assign weights to patterns based on a conjecture that the *number of times an API usage pattern appears in the code* provides a more meaningful metric than the number of times that code executes [2].

Most previous work on statistical trace analyses considered raw traces consisting of raw event streams [5], [2] or event pairs [31], [29]. In contrast, our work summarizes samples that already represent summarized abstract traces, represented as automata. In this section, we present new approaches to statistical summarization that exploit the structure already present in these automata.

Our Summarization phase combines the results produced during the analysis of the clients in the code base. It can also consider a number of different client code bases. Due to its statistical nature, summarization does not maintain the soundness guarantee of the trace collection phase. Namely, it might erroneously identify correct behaviors as spurious ones, and remove them.

In the sequel, we assume without loss of generality, that the observed traces are given via a set $\mathcal{I}$ of deterministic finite automata (if nondeterministic automata were produced, we add a determinization step). The output of summarization consists of a ranked set of $k \leq |\mathcal{I}|$ automata, where each of the k represents a candidate API specification.

A. Union Methods

Naive Union: The naive approach outputs the union of all the automata in $\mathcal{I}$ as the API specification, without any noise reduction. This approach treats all traces uniformly, regardless of their frequency. Moreover, it does not distinguish between different ways in which the API is used.

Weighted Union: A better straightforward statistical approach uses a weighted union of the input automata to identify and eliminate infrequent behaviors. Specifically, we form the union automaton for all input automata, labelling each transition with the count of the number of input automata which contain it. Given this labelled automaton, one can apply any number of heuristics to discard transitions with low weights. Our implementation takes a threshold parameter f ($0 \leq f \leq 1$) and discards any transitions whose weight is less than f times the number of input automata.

B. Clustering

When a code base contains several independent patterns of API usage, these patterns may interfere to defeat union-based noise reduction. Instead, we partition the input into clusters of "similar" automata, and eliminate noise in each cluster independently.

We use a simple clustering algorithm based on a notion of automata *inclusion*. Automaton A *includes* automaton B iff $\mathcal{L}(A) \supseteq \mathcal{L}(B)$. The *include* relation induces a partial order on the set of automata. Each "maximal" element (automaton) w.r.t. this order represents a cluster consisting of all the automata included in it. Our algorithm forms clusters based on inclusion, and then applies the weighted union technique independently in each cluster.

Example 5.1: Consider Fig. 8. Each of the automata (a) and (b) represents a possible usage of the `Signature` API in some code base. Assume that each of them was observed numerous times. A weighted union of them with any reasonable threshold will return the right most automaton in Fig. 8, where the two usage patterns are combined. A clustered union, on the other hand, will identify that these are two different usage patterns, and will return (a) and (b) as two clusters.

Assume further that the code base also produced the automaton (c) of Fig. 8. Automaton (c) refers to the same usage pattern as (a), but contains an additional transition from the initial state, which represents an invocation of `initSign`. This transition is erroneous in this particular usage pattern, although it is not erroneous in the global view of the API, since an invocation of `initSign` from the initial state is a legal behavior in another context – that of pattern (b). In the weighted union, this transition simply increases the weight of the bold edge by 1, but it is not recognized as an error. Our clustered weighted union, on the other hand, recognizes that (c) belongs to the cluster of (a), and as a result it identifies and removes the erroneous transition.

[2]An empirical evaluation of this conjecture falls outside the scope of this paper, but would be an interesting direction for future work.

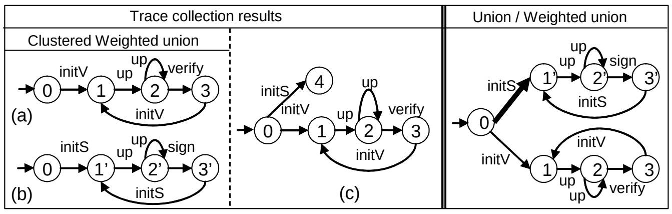


Fig. 8. Summarization: Clustered Weighted Union Vs. Weighted Union.

Note that after transitions are removed, the *include* relation can change as disparate clusters sometimes converge. As such, we iterate the entire process, starting from the clustering, until reaching a fixpoint. As a post-pass, an entire cluster can be removed as noise based on further statistical analysis.

VI. Refining Mining Results using Inspection

When performing mining, some of the loss of precision is due to the (essential) abstraction of the history. Spurious behavior that is included in the mined automata due to the history abstraction sometimes eludes the statistical summarization approaches since it repeats itself in multiple automata. Thus, other techniques are needed to deal with such noise.

In this section, we describe a number of approaches for refining the results obtained through mining. These approaches are based on making the history abstraction more precise. Our refinement is based on the observation that the mined automata indicate where more analysis effort could help make the results more precise. Namely, we select candidate paths from the mined automata and use *inspection* to check if those paths represent correct usage patterns of the API. If a path turns out to be spurious, we refine the abstraction in order to eliminate that path.

A. Static Inspection

Static inspection can either be performed from the client side or the component side.

1) Static Client Inspection: Static client inspection statically checks whether a given scenario is present in the code base. Checking for the absence of a scenario is also known as *typestate verification* (e.g., [11]). Since checking for a specific scenario only requires recording the current state of the typestate property, and not a more elaborate abstraction of the history, it is generally cheaper than mining. Therefore, the checking procedure can use more precise (and thus costly) heap abstractions and be used to prune spurious scenarios that are observed as absent from the code base.

2) Static Component Inspection: Static component inspection statically checks whether a given scenario might produce an error when executed over the component.

The extreme case of static component inspection is that of [1] and [23] which exhaustively (and conservatively) explore all client scenarios and the resulting component behaviors.

B. Dynamic Inspection

While static inspection is limited, as it still requires some heap abstraction, dynamic inspection has the advantage that it can also identify imprecision that results from the heap abstraction.

Similarly to static inspection, dynamic inspection also comes in two flavors: client side and component side.

- dynamic client-side inspection checks whether a given usage-scenario may exist in a given code base (under-approximation). This can be implemented by instrumenting client-code to record various events. This approach is applied by dynamic mining tools such as Daikon [10].
- dynamic component side inspection checks whether a given usage-scenario may execute without failure over the component. This is an under-approximation, as the component may fail this sequence only on specific environment conditions (e.g., only fail the sequence on Mondays). It can be performed without the code of the component, but requires an ability to execute it. This is commonly referred to as unit-testing.

C. Selection of Paths for Inspection

When a scenario is identified as spurious, the abstraction used for mining can be locally refined in order to eliminate the spurious scenario. The question remaining is how to identify spurious paths, namely, how to select paths for inspection.

There are a number of approaches for selecting paths for inspection. The naive approach is to simply try all acyclic paths in the mined automaton, or some bounded unrolling of the cyclic paths. When the final result of mining is a weighted automaton, spurious paths/edges may be identified as the ones that have a relatively low weight.

Example 6.1: Consider the `Signature` API. Suppose that the mined automaton, mined with the past abstraction, is the one depicted in Fig. 9(a). We now enumerate all acyclic paths in the mined automaton of Fig. 9(a):

(i) `initSign; update; sign; initSign`
(ii) `initSign; update; verify; initVerify`
(iii) `initVerify; update; verify; initVerify`
(iv) `initVerify; update; sign; initSign`

We now run inspection, say static client-side inspection (typestate verification), to try and verify the absence of each one of the sequences (i)-(iv). This is done by specifying the sequence itself as an input typestate property for the verifier.

Since the typestate verifier does not need to record histories, we can employ the solver with more precise abstractions, and observe the fact that both (ii) and (iv) are sequences that cannot occur in the client program.

Based on this information, we can locally increase the context for the past abstraction such that it is able to distinguish the valid sequences (i) and (iii) from the invalid ones (ii) and (iv).

D. Refinement based on Abstraction Merge Points

A more sophisticated approach for refinement, which also uses inspection, is based on the merge points of the abstraction. Recall that our past-future abstractions merge automata states based on their ingoing/outgoing sequences. These merge points are responsible for the overapproximation of the specification. As such, we aim at identifying merge points which are potentially responsible for the inclusion of spurious behaviors.

Consider the past abstraction. Similar ideas are applicable for the future abstraction as well. In the k-past abstraction, an automaton state q that has (at least) two ingoing paths of length k labelled with the same sequence represents a merge point. The joint suffix of length k of the two ingoing paths is responsible

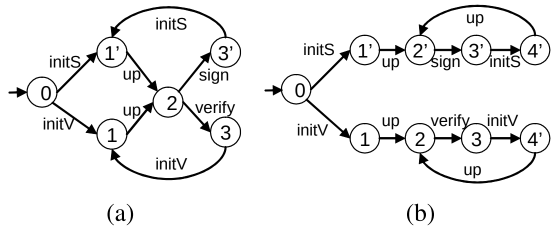


Fig. 9. (a) 1-Past abstraction; and (b) 2-Past abstraction.

for the merge of the states that resulted in q. For example, in Fig. 9(a), state 2 is a merge point of the past abstraction as it has two ingoing sequences (`initSign; update`, `initVerify; update`). The suffix `update` of these sequences is responsible for the merge.

If the state q that represents a merge point also has (at least) two different outgoing behaviors, then this means that one originated while tracking the first ingoing sequence and the second originated when tracking the other. The merge introduced the additional two combinations of ingoing and outgoing sequences.

For example, in Fig. 9(a), state 2 has two outgoing sequences: `sign` which originated after tracking the ingoing sequence `initSign; update`, and `verify` which originated after tracking the ingoing sequence `initVerify; update`. The merge introduced the (erroneous) combinations of `initSign; update` and `verify` and of `initVerify; update` and `sign`.

States that have multiple ingoing and outgoing sequences are therefore considered *suspicious* merge points and are candidates for inspection. When a suspicious merge point q is encountered, the validity of the merge is inspected by checking if all the combinations of an ingoing sequence and an outgoing sequence are legitimate. If one of these combinations turns out to be illegal, refinement of q is needed. This can be achieved by increasing the context of the past abstraction to reflect the difference between the two ingoing sequences of q.

Example 6.2: Consider the `Signature` API. Suppose that the mined automaton, mined with the past abstraction, is the one depicted in Fig. 9(a). In this case, state 2 is a suspicious merge point as it has both two different ingoing sequences (`initSign; update`, `initVerify; update`) and two outgoing sequences (`sign`, `verify`). Indeed, inspection shows that the concatenation of `initSign; update` and `verify`, as well as the concatenation of `initVerify; update` and `sign`, results in a spurious path. Thus, refinement increases the context of the past abstraction to 2, as length 2 reflects the difference between the ingoing sequences of state 2. This prevents the spurious merge and the resulting automaton is depicted in Fig. 9(b).

Note, however, that this kind of refinement does not guarantee that the "bad" state q will be split in the next iteration of mining (with the extended context), since there can be other ingoing sequences of the increased length that will cause q to be merged again. For example, if in the `Signature` example state 2 has a selfloop with the `update` event (i.e., the code base allows any number of `update` events before `verify` or `sign`), then no finite context will prevent the merge.

Suspicious merge points are found as follows. First, an automaton state that has (at least) two ingoing paths labelled with the same sequence of length k is found by a BFS from the initial state. Whenever a new state is encountered, we check if it has at least two ingoing transitions. If it does, then it has (at least) two ingoing paths labelled with the same suffix of length k (due to the past-property). For example, in Fig. 9(a), state 2 has two ingoing transitions, and indeed these represent two ingoing paths labelled with the same suffix of length 1.

Note that the full sequences that label the ingoing paths that lead from the initial state to such a state cannot be identical, although they end with an identical suffix. This is because at latest the ingoing paths collide at the initial state, and since the automaton is deterministic, the transitions where the paths collide must be labelled by different events. In the above example the ingoing paths of state 2 collide at the initial state and the corresponding transitions are indeed labelled by different events: `initSign` and `initVerify`. Moreover, the two different ingoing sequences can be found by a backward traversal of the BFS tree until the initial state is encountered.

Let q be such an automaton state that has two different ingoing sequences. To check if q also has at least two different outgoing behaviors (and find them), another BFS is applied, starting from q. There are 3 possibilities.

(a) The search ends without finding any state with more than one outgoing transition. In this case, no inspection is needed since q has only one outgoing behavior, thus the merge did not add any behavior.
(b) The search reaches a state q' (possibly q itself) that has at least two outgoing transitions. In this case, the path from q to q' followed by the two outgoing transitions of q' defines two different outgoing behaviors of q. This is the case in Fig. 9(a), where state 2 itself has two outgoing transitions: one labelled `sign` and one labelled `verify`.
(c) The search reaches a previously visited state q'. This means that a simple loop was encountered, one that has no outgoing transitions (except for the ones along the loop). In this case different unwindings of the loop define different behaviors that originate in q.

Similar ideas can be used on the nondeterministic automata returned by future merge.

VII. Experimental Results

We have implemented a prototype of our analysis based on the WALA analysis framework [27] and the typestate analysis framework of [11]. Our analysis builds on a general Reps-Horwitz-Sagiv (RHS) IFDS tabulation solver implementation [25]. We extended the RHS solver to support dynamic changes and merges in the set of dataflow facts. The pointer analysis adds one level of call-string context to calls to various library factory methods, `arraycopy`, and `clone` statements, which tend to badly pollute pointer flow precision if handled without context-sensitivity. The system uses a substantial library of models of native code behavior for the standard libraries.

A. Benchmarks

Table II lists the benchmarks used in this study. Each of the benchmarks `bobalice`, `js-chap13`, and `j2ns`, is a set of examples taken from a book on Java security [24]. `flickrapi` is an open source program providing a wrapper over flickr APIs, as well as some utilities using it. `ganymed` is a library implementing the SSH-2 protocol in pure Java; the library comes

Num	Benchmark	Classes	Methods	Bytecodes	Contexts	Clients
1	aamfetch	635	2544	246284	3316	2
2	bobalice	259	1318	71048	1917	2
3	crypty	450	2138	127130	2794	1
4	flickrapi	123	423	26607	527	2
5	ganymed	121	649	49232	919	4
6	j2ns	944	4817	399402	6570	5
7	javacup	373	2000	122592	2981	2
8	javasign	111	473	45670	740	11
9	jbidwatcher	64	525	18717	269	9
10	jfreechart	654	2644	250718	3457	18
11	jlex	89	317	25261	382	2
12	jpat-p	374	2043	141649	5570	1
13	JPDStore	109	359	23040	418	2
14	js-chap13	661	2795	259273	3770	6
15	privatray	175	665	56543	876	1
16	tinysql	701	3019	277881	3980	2
17	tvla	643	2572	249243	3355	3

TABLE II
BENCHMARKS.

with examples and utility programs that use it. `javacup` and `jlex` are a parser generator and lexical analyzer, respectively, for Java. `jbidwatcher` is an online auction tool. `jfreechart` is a Java chart library. `tinysql` is a lightweight Java SQL engine. `tvla` is a static analysis framework.

The table reports size characteristics restricted to methods discovered by on-the-fly call-graph construction. The call graph includes methods from both the application and the libraries; for many programs the size of the program analyzed is dominated by the standard libraries. The table also reports the number of (method) contexts in the call graph (the context-sensitivity policy models some methods with multiple contexts). The last column shows the number of client programs for each benchmark.

Using these clients, we applied our prototype to mine specifications for a number of APIs, as described in more detail in the next section. Our implementation employs standard automata minimization, and our results always refer to minimized automata.

Our most precise solvers (APFocus/Past/Exterior and APFocus/Future/Exterior) run in less than 30 minutes per benchmark. Our less precise solvers run in about half the time. This performance seems reasonable for non-interactive mining of a code base.

B. Results

Our evaluation focuses first on three dimensions for abstract trace collection:

- The heap abstraction (Sec. IV-B.1): Base vs. APFocus
- The history abstraction (Sec. IV-B.3): Past vs. Future
- The merge criteria (Sec. IV-B.3): Total vs. Exterior merge

Table III characterizes the specifications generated by our analysis, varying the abstractions along these three dimensions. Each row summarizes the result for a specific API across a number of benchmarks.

Some APIs appear in several separate benchmarks, while others appear in several programs contained within the same benchmark. The `Auth` and `Photo` APIs are used in benchmark 4. `Channel`, `ChannelManager`, `Connection`, `Session`, and `TransportManager` are used in benchmark 5. `Cipher` is used in benchmarks 1, 3, 14, and 15. `KeyAgreement` is used in benchmark 2. `LineAndShapeRenderer` is used in benchmark 10. `MessageDigest` is used in benchmarks 1, 13, and 15. `PrintWriter` is used in benchmarks 7 and 11. `Signature` is used in 6 and 8. `URLConnection` is used in benchmark 9.

Each column of the table corresponds to a combination of a heap abstraction, history abstraction, and merge criterion. When using Total merge, we only show results for Past history abstraction; results for Future would be similar under this aggressive merge criterion. All results in the table reflect the Naive Union summarization (Sec. V-A), which preserves all information collected by the trace collectors. This allows to compare the quality of different abstract trace collectors without interference from summarization effects.

The table reports, for each mined specification, the number of states and transitions, and the average degree (number of outgoing edges) of states in the specification. Intuitively, the degree of a node represents the number of possible legal operations from a given state. Since all specifications in the table overapproximate client behavior, a smaller degree represents a better specification since it admits fewer spurious behaviors. Note that the different overapproximations may be incomparable in terms of the languages they accept; that is, we cannot, in general, rank the mined specifications based on a simulation ordering. Note also that average degree is a relative metric; its absolute value depends on the number of observable events in the specification.

The results show across the board that precise alias analysis is significant; the mined specifications appear significantly more permissive under Base aliasing than under APFocus. Exterior merge improves over total merge frequently when using Base aliasing, and occasionally under APFocus aliasing. When using the most precise APFocus aliasing and exterior merge, the distinction between past and future abstractions vanishes in these experiments, although they behave significantly differently under Base aliasing.

For some specifications, we were able to track the usage pattern manually by inspecting the client code. For others, the complexity of the client code (or even lack of Java source code) prevented us from understanding the client API usage based on inspection. Based on manual inspection, we were able to verify that for 5 out of the 14 APIs, the most precise analysis generated the ideal specification, even with the naive union summarization. These APIs appear in bold in the table.

We additionally collected specifications with weighted summarization for each benchmark. We do not report densities obtained by weighted summarization, as the specification density will depend directly on the threshold parameter provided as input. We note based on inspection that a user-provided threshold of 1/2 for the weighted union algorithm yields improved specifications for several APIs. In practice, we expect a user would provide feedback to iteratively tune the threshold as desired.

We also ran the cluster-based summarization for all specifications. For several APIs, clustering correctly identified a number of independent usage patterns of the API in our code base. In particular, the specification obtained for `Cipher` using the naive union collector was polluted by calls to irrelevant methods. Using the combination of clustering and weighted algorithms, we obtained the "ideal" specification expected by a human.

Fig. 10 shows the output of our tool for the `Signature` API. This API was mined using APFocus/Past/Exterior collector, and summarized using the naive union summarization. Note that the specification correctly disambiguates two use cases, *verify* and *sign*. An approach based on event pairs (e.g. [29], [31]) could

	Base/Past/Total			Base/Past/Ext			Base/Future/Ext			APF/Past/Total			APF/Past/Ext			APF/Future/Ext		
API	**states**	**edges**	**avg. degree**	**states**	**edges**	**avg. degree**	**states**	**edges**	**avg. degree**	**states**	**edges**	**avg. degree**	**states**	**edges**	**avg. degree**	**states**	**edges**	**avg. degree**
Auth	2	3	1.50	2	3	1.5	2	3	1.5	2	2	1.00	2	2	1.00	2	2	1.00
Channel	2	6	3.00	3	6	2.00	3	6	2.00	3	3	1.00	3	3	1.00	3	3	1.00
ChannelMgr	2	11	5.50	5	18	3.60	6	19	3.17	4	7	1.75	5	9	1.80	5	9	1.80
Cipher	1	5	5.00	4	14	3.50	6	12	2.00	7	10	1.43	7	10	1.43	7	10	1.43
Connection	3	12	4.00	4	12	3.00	4	12	3.00	5	7	1.40	5	7	1.40	5	7	1.40
KeyAgreement	2	5	2.50	4	6	1.50	4	6	1.5	4	3	0.75	4	3	0.75	4	3	0.75
LineAndShape	3	12	4.00	6	15	2.50	6	15	2.50	6	8	1.33	6	8	1.33	6	8	1.33
MsgDigest	1	2	2.00	2	2	1.00	2	2	1.00	2	2	1.00	2	2	1.00	2	2	1.00
Photo	1	12	12.00	1	12	12.00	1	8	8.00	8	8	1.00	8	8	1.00	8	8	1.00
PrintWriter	1	3	3.00	2	3	1.50	2	3	1.50	6	11	1.83	3	5	1.67	3	5	1.67
Session	2	7	3.50	5	10	2.00	5	10	2.00	5	4	0.80	5	4	0.80	5	4	0.80
Signature	2	8	4.00	5	12	2.40	5	12	2.40	4	6	1.50	4	6	1.50	4	6	1.50
TransportMgr	9	24	2.67	2	19	9.50	8	27	3.38	9	26	2.89	9	24	2.67	9	24	2.67
URLConnection	2	9	4.50	4	10	2.5	3	6	2	4	7	1.75	NA	NA		NA	NA	
Average			**4.08**			**3.46**			**2.57**			**1.39**			**1.33**			**1.33**
Std dev			**2.54**			**3.22**			**1.71**			**0.56**			**0.52**			**0.52**

TABLE III

CHARACTERISTICS OF OUR MINED SPECIFICATIONS WITH VARYING DATA COLLECTORS. FOR EVERY MINED SPECIFICATION DFA, WE SHOW THE NUMBER OF STATES, EDGES, AND THE DENSITY OF THE DFA. APIS FOR WHICH THE MOST PRECISE ANALYSIS GENERATED THE IDEAL SPECIFICATION APPEAR IN BOLD.

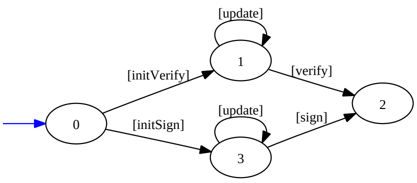


Fig. 10. Mined Specification for java.security.Signature, obtained with APFocus/Past/Exterior.

not distinguish these two cases.

Fig. 11 shows the output of our tool for the `ganymed Session` API under two collector settings, and summarized using the naive union summarization. This figure shows a typical qualitative difference between Base aliasing and APFocus. Fig. 12 shows a similar comparative output of our tool for the `KeyAgreement` API.

A small gallery of mined specifications appears in an informal online supplement to this paper [12].

C. Discussion

Generally, the mined specification are useful in many settings. For example, we suggest the following usage scenarios:

- program understanding: understanding a component by the way it is used by a client, and understanding an unknown client by the way it is using known components.
- regression: where new code added to a code-base has to conform to the way the code-base is using key APIs.
- identifying deviant behaviors that do not comply with the specification as likely bugs, and possibly even used for automatically fixing code by making it conform to common usage patterns.
- finding existing code fragments that bring the program to a specified desired state (a natural, more powerful, extension of [21]).

The quality of the mined specification should be evaluated with respect to its particular usage. For example, a specification mined for the purpose of program understanding should be human-readable, where a specification mined for identifying deviant behaviors may ignore such a requirement.

Our experiments indicate that having both a precise-enough heap abstraction and a precise-enough history abstraction are required to be able to mine a reasonable specification for either of the aforementioned usage scenarios.

Without such precise abstractions, the collected abstract histories might deteriorate to a point in which no summarization algorithm will recover the lost information. For example, the specification mined for the `Photo` API using the Base heap abstraction has a single state. This means that the specification does not contain any temporal information on the ordering of events. (Similarly for `PrintWriter` under Base/Past/Total.)

1) Soundness: All of the results in Table III were obtained when our analysis was run to completion, and are therefore guaranteed to be an over-approximation of the behavior present in the analyzed code base. In contrast, it is also possible to employ our analysis with a predetermined timeout (or with e.g., a small limited heap size). In such cases, the specification obtained using the analysis will not over-approximate code base behavior, but may still help understand some behaviors. For example, when running on TVLA, we mined a partial but interesting description of the way `tvla.Engine` is used in the code base.

2) Limitations: Our prototype shows encouraging results, but due to several limitations, does not yet suffice for deployment in an industrial tool.

Our implementation currently considers all methods of an API as equally interesting. In general, this pollutes specifications with calls to pure methods that do not change the state of the component. When library code is available, one might analyze the library to identify pure methods and treat them specially in both abstract trace collection and summarization. In the absence of library code, we envision a feedback loop involving user input, specifying methods that should be ignored.

In some cases, the specifications mined by our approach are too detailed, and track distinctions that hold no interest to the end

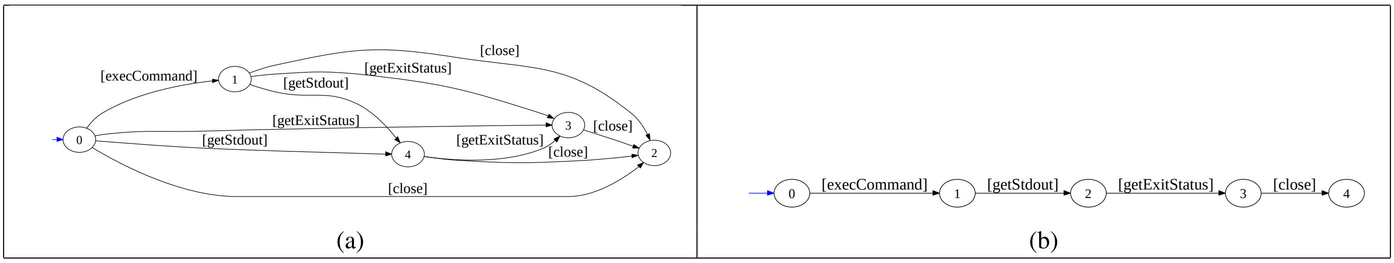


Fig. 11. Session API with Past/Exterior merge and (a) Base aliasing, (b) APFocus aliasing.

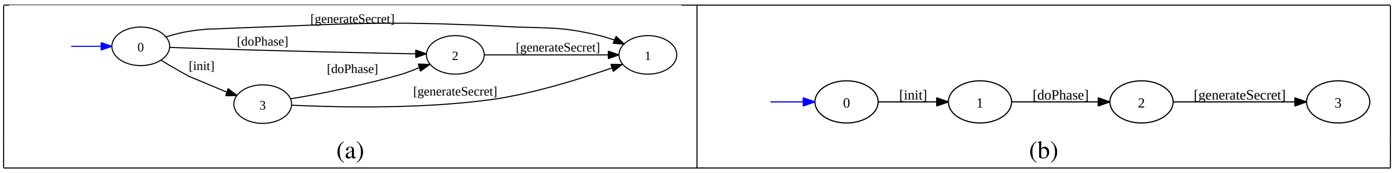


Fig. 12. KeyAgreement API with Past/Exterior merge and (a) Base aliasing, (b) APFocus aliasing.

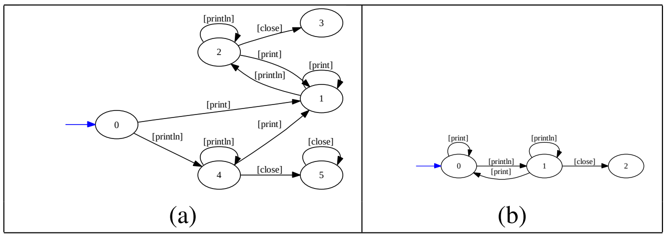


Fig. 13. PrintWriter API with APFocus aliasing, and past (a) total merge, and (b) exterior merge.

user. For example, the specification we mine for `PrintWriter`, shown in Fig. 13, records some artificial temporal ordering between `print` and `println`. We'd expect these problems to resolve themselves with a larger input corpus; if not, a practical tool would probably resort to user feedback to refine results.

Our current implementation does not scale to code bases larger than roughly a few tens of thousands of lines in reasonable time and space (depending on properties of the dataflow solution). The scaling problem is fundamental to all whole program analyses, and does not stem primarily from the particular history abstractions introduced in this paper. In the future, we plan to explore how this technique could be turned into a modular one in the spirit of [32], which we believe is a crucial step for a practical implementation.

Our current prototype restricts itself to specifications involving a single object; however, many interesting specifications involve multiple types and objects. The ideas presented in this paper can apply to components that involve multiple objects, but the scalability and precision questions remain open.

Despite these limitations, we are encouraged by the results obtained with our current implementation, which show the strength of our heap and history abstractions, as well as our summarization algorithms. We also expect these abstractions to be useful in the context of other analyses that track temporal sequences.

VIII. Related Work

Dynamic Analysis: When it is feasible to run a program with adequate coverage, dynamic analysis represents the most attractive option for specification mining, since dynamic analysis does not suffer from the difficulties inherent to abstraction.

Cook and Wolf [5] consider the general problem of extracting an FSM model from an event trace, and reduce the problem to the well-known *grammar inference* [13] problem. Cook and Wolf discuss algorithmic, statistical, and hybrid approaches, and present an excellent overview of the approaches and fundamental challenges. This work considers mining automata from uninterpreted event traces, attaching no semantic meaning to events.

Ammons et al. [2] infer temporal and data dependence specifications based on dynamic trace data. This work applies sophisticated probabilistic learning techniques to boil traces down to collections of finite automata which characterize the behavior. Lo and Khoo [19] extend Ammons' work, and employ machine learning techniques in order to mine probabilistic temporal specifications from dynamic execution traces.

Whaley et al. [30] present a two-phased approach to mining temporal API interfaces, combining a static component-side safety check with a dynamic client-side sequence mining. The static analysis is extremely simple, and used primarily to restrict the dynamic search of temporal sequences, rather than to directly infer specifications. This work presents several insights on how to refine results, based on side-effect free methods, and partitioning methods based on how they access fields. We plan to incorporate these insights into a future version of our analysis.

The Perracotta tool [31] addressed challenges in scaling dynamic mining of temporal properties to large code bases. This tool mines traces for two-event patterns with an efficient algorithm, and relies on heuristics to help identify interesting patterns.

Livshits and Zimmerman [18] mine a software repository revision history to find small sets of methods whose usage may be correlated. This analysis is simple and scalable; in contrast to ours, it does not consider temporal ordering nor aliasing. In a second (dynamic) phase, the system checks whether candidate temporal patterns actually appear in representative program traces. Our analysis technology could perhaps be employed in a similar architecture to provide a more effective first phase of mining.

Demsky and Rinard [8] present a dynamic mining approach and tool based on the concept of *roles*. As in Kuncak et al. [15], this work starts with the hypothesis that aliasing relationships between objects define roles, or relevant typestates. Based on this observation, they present a graphical tool which allows the user to navigate role relationships derived by analysis of a dynamic trace. The user can guide the tool with respect to role separation criteria and other heuristics, in order to navigate to a meaningful specification. This work also incorporates the notion of state changes based solely on method calls on a particular object, similar the traces presented in our concrete semantics.

Dallmeier et. al. [7] use a dynamic analysis to extract object behavior models (similar to our temporal specifications) from program executions. Their approach uses a preceding static analysis that classifies each method as a mutator (modifies object state) or an inspector (does not affect object state). The mutator methods are then instrumented to record the resulting object state.

Mariani and Pezzè [22] use dynamic analysis to detect COTS component incompatibilities. They extract interaction models between components in the form of finite-state automata representing the sequences of interactions triggered by invoking services. The automata are extracted by an inference algorithm which works incrementally on a set of positive samples (traces). Their algorithm identifies subsequences of a new trace in the current automaton and connects the identified subsequences to include the new trace in the automaton. It thus resembles our past abstraction.

In [20], the authors use annotated FSMs to represent individual failure executions of enterprise applications encountered at run time (as a part of a self-protecting technique). The annotated FSMs are augmented with weights that indicate the relevance of the transitions with respect to the identification of a failure. A failure context is then generated from the weighted FSM.

A number of projects mine specifications in the form of *dynamic invariant detection*. Daikon [10] instruments a running program and infers invariants based on values of variables in representative program traces, typically discovering method preconditions, postconditions, and loop invariants. Daikon does not explicitly target temporal sequences, but may apply to temporal properties that are reflected by variable invariants at particular program points. DIDUCE [14] combines invariant detection and checking in a single tool, aimed to help diagnose failures. As a program runs, DIDUCE maintains a set of hypothesized invariants, and reports violations of these invariants as they occur.

Component-side Static Analysis: In component-side static analysis, a tool analyzes a component's implementation, and infers a specification that ensures the component does not fail in some predetermined way, such as by raising an exception. In contrast, client-side mining produces a specification that represents the usage scenarios in a given code-base. The two approaches are complementary, as demonstrated in [30].

Recent years have seen a number of sophisticated component-side static analyses. Alur et al. [1] use Angluin's algorithm together with a model-checking procedure to learn a permissive interface of a given component. Gowri et al. [23] use static mining to learn a permissive first-order specification involving objects, their relationships, and their internal states.

Client-side Static Analysis: A few papers have applied static analysis to client-side specification mining.

Engler et al. [9] use various static analyses to identify common program behaviors, and consider deviations from these behaviors as bugs. Their approach automatically establishes certain invariants as likely *beliefs*, and the tool searches for bugs by finding code sequences that violate these invariants. The tool searches for invariants based on a set of standard templates, and filters potential specifications with a statistical measure (z-ranking). Their approach has been highly effective in finding bugs in system code.

Weimer and Necula [29] use a simple, lightweight static analysis to infer simple specifications from a given codebase. Their insight is to use exceptional program paths as negative examples for correct API usage. We believe that our approach could also benefit from using exceptional paths as negative examples. Weimer and Necula learn specifications that consist of pairs of events $\langle a, b\rangle$, where a and b are method calls, and do not consider larger automata. They rely on type-based alias analysis, and so their techniques should be much less precise than ours. On the other hand, their paper demonstrates that even simple techniques can be surprisingly effective in finding bugs.

Mandelin et al. [21] use static analysis to infer a sequence of code (*jungloid*) that shows the programmer how to obtain a desired target type from a given source type (a *jungloid query*). This code-sequence is only checked for type-safety and does not address the finer notion of typestate. In contrast, our approach focuses on mining temporal specifications.

Wasylkowski, Zeller, and Lindig [28] use an intraprocedural static analysis to automatically mine object usage patterns and identify usage anomalies. Their approach is based on identifying usage patterns. In contrast, our approach mines temporal specifications that over-approximate the usage scenarios in a code-base.

Other Static Analyses: [16] presents a model-extraction technique and extracts both the object relationships and a model of their interactions. This approach requires user annotation that associates a "token" with every object of interest and uses static analysis to infer the relationships and interactions between tokens. In contrast, our approach currently focuses only on typestate specifications, but is fully automatic.

Lie et al. [17] present an approach to extract state transition models using an extensible compiler, xg++. In this work, the user specifies patterns corresponding to state variables and operations relevant to a particular protocol. Based on this specification, the compiler slices the program to elide irrelevant statements, and then performs a simple user-guided translation to output the model in a desired form, suitable for input to a model-checker. This work targets low-level cache coherency protocols implemented in C.

IX. Conclusion

To our knowledge, this paper presents the first study attempting client-side temporal API mining with static analysis beyond trivial alias analysis and history abstractions. Static analysis improves coverage over dynamic analysis both by exploring all paths for a single program, and by expanding the corpus of code amenable to automated analysis. We plan to conduct further research into modular analysis techniques and improved summarization heuristics, to move closer to practical application of this technology.

References

[1] R. Alur, P. Cerny, P. Madhusudan, and W. Nam. Synthesis of interface specifications for Java classes. *SIGPLAN Not.*, 40(1):98–109, 2005.

[2] G. Ammons, R. Bodik, and J. R. Larus. Mining specifications. In *POPL '02: Proceedings of the 29th ACM SIGPLAN-SIGACT symposium on Principles of programming languages*, pages 4–16, New York, NY, USA, 2002. ACM Press.

[3] L. O. Andersen. *Program Analysis and Specialization for the C Programming Language*. PhD thesis, DIKU, Univ. of Copenhagen, May 1994. (DIKU report 94/19).

[4] D. Chase, M. Wegman, and F. Zadeck. Analysis of pointers and structures. In *Proc. ACM Conf. on Programming Language Design and Implementation*, pages 296–310, New York, NY, 1990. ACM Press.

[5] J. E. Cook and A. L. Wolf. Discovering models of software processes from event-based data. *ACM Trans. Softw. Eng. Methodol.*, 7(3):215–249, 1998.

[6] P. Cousot and R. Cousot. Abstract interpretation: a unified lattice model for static analysis of programs by construction or approximation of fixpoints. In *POPL '77: Proceedings of the 4th ACM SIGACT-SIGPLAN symposium on Principles of programming languages*, pages 238–252, New York, NY, USA, 1977. ACM Press.

[7] V. Dallmeier, C. Lindig, A. Wasylkowski, and A. Zeller. Mining object behavior with adabu. In *WODA '06: Proceedings of the 2006 international workshop on Dynamic systems analysis*, pages 17–24, New York, NY, USA, 2006. ACM.

[8] B. Demsky and M. Rinard. Role-based exploration of object-oriented programs. In *ICSE '02: Proceedings of the 24th International Conference on Software Engineering*, pages 313–324, New York, NY, USA, 2002. ACM.

[9] D. Engler, D. Y. Chen, S. Hallem, A. Chou, and B. Chelf. Bugs as deviant behavior: a general approach to inferring errors in systems code. In *SOSP '01: Proceedings of the eighteenth ACM symposium on Operating systems principles*, pages 57–72, New York, NY, USA, 2001. ACM Press.

[10] M. D. Ernst, J. Cockrell, W. G. Griswold, and D. Notkin. Dynamically discovering likely program invariants to support program evolution. *IEEE Transactions on Software Engineering*, 27(2):99–123, Feb. 2001.

[11] S. Fink, E. Yahav, N. Dor, G. Ramalingam, and E. Geay. Effective typestate verification in the presence of aliasing. In *ISSTA '06: Proceedings of the 2006 international symposium on Software testing and analysis*, pages 133–144, New York, NY, USA, 2006. ACM Press.

[12] Gallery of mined specification. http://tinyurl.com/23qct8 or http://docs.google.com/View?docid=ddhtqgv6_10hbczjd.

[13] E. M. Gold. Language identification in the limit. *Information and Control*, 10:447–474, 1967.

[14] S. Hangal and M. S. Lam. Tracking down software bugs using automatic anomaly detection. May 2002.

[15] V. Kuncak, P. Lam, and M. Rinard. Role analysis. In *Proc. ACM Symp. on Principles of Programming Languages*, Portland, January 2002.

[16] P. Lam and M. Rinard. A type system and analysis for the automatic extraction and enforcement of design information. In *ECOOP*, 2003.

[17] D. Lie, A. Chou, D. Engler, and D. L. Dill. A simple method for extracting models for protocol code. In *ISCA '01: Proceedings of the 28th annual international symposium on Computer architecture*, pages 192–203, New York, NY, USA, 2001. ACM Press.

[18] V. B. Livshits and T. Zimmermann. Dynamine: Finding common error patterns by mining software revision histories. In *Proceedings of the 13th ACM SIGSOFT International Symposium on the Foundations of Software Engineering (FSE-13)*, pages 296–305, Sept. 2005.

[19] D. Lo and S.-C. Khoo. SMArTIC: towards building an accurate, robust and scalable specification miner. In *SIGSOFT '06/FSE-14: Proceedings of the 14th ACM SIGSOFT international symposium on Foundations of software engineering*, pages 265–275, New York, NY, USA, 2006. ACM.

[20] D. Lorenzoli, L. Mariani, and M. Pezzè. Towards self-protecting enterprise applications. In *18th IEEE International Symposium on Software Reliability Engineering (ISSRE 2007)*, November 2007.

[21] D. Mandelin, L. Xu, R. Bodik, and D. Kimelman. Jungloid mining: helping to navigate the API jungle. In *PLDI '05: Proceedings of the 2005 ACM SIGPLAN conference on Programming language design and implementation*, pages 48–61, New York, NY, USA, 2005. ACM Press.

[22] L. Mariani and M. Pezzè. Dynamic detection of COTS components incompatibility. *IEEE Software*, 24(5):76–85, September/October 2007.

[23] M. G. Nanda, C. Grothoff, and S. Chandra. Deriving object typestates in the presence of inter-object references. In *OOPSLA '05: Proceedings of the 20th annual ACM SIGPLAN conference on Object oriented programming, systems, languages, and applications*, pages 77–96, New York, NY, USA, 2005. ACM Press.

[24] M. Pistoia, D. Reller, D. Gupta, M. Nagnur, and A. K. Ramani. *Java 2 Network Security*. Prentice Hall PTR, Upper Saddle River, NJ, USA, second edition, August 1999.

[25] T. Reps, S. Horwitz, and M. Sagiv. Precise interprocedural dataflow analysis via graph reachability. In *Proc. ACM Symp. on Principles of Programming Languages*, pages 49–61, 1995.

[26] A. Salcianu and M. Rinard. Purity and side effect analysis for Java programs. In *VMCAI'05: Proceedings of the 6th International Conference on Verification, Model Checking, and Abstract Interpretation*, 2005.

[27] WALA: The T. J. Watson Libraries for Analysis. http://wala.sourceforge.net.

[28] A. Wasylkowski, A. Zeller, and C. Lindig. Detecting object usage anomalies. In *ESEC-FSE '07: Proceedings of the the 6th joint meeting of the European software engineering conference and the ACM SIGSOFT symposium on The foundations of software engineering*, pages 35–44, New York, NY, USA, 2007. ACM.

[29] W. Weimer and G. Necula. Mining temporal specifications for error detection. In *TACAS*, 2005.

[30] J. Whaley, M. C. Martin, and M. S. Lam. Automatic extraction of object-oriented component interfaces. In *Proceedings of the International Symposium on Software Testing and Analysis*, pages 218–228. ACM Press, July 2002.

[31] J. Yang, D. Evans, D. Bhardwaj, T. Bhat, and M. Das. Perracotta: mining temporal API rules from imperfect traces. In *ICSE '06: Proceeding of the 28th international conference on Software engineering*, pages 282–291, New York, NY, USA, 2006. ACM Press.

[32] G. Yorsh, E. Yahav, and S. Chandra. Symbolic summarization with applications to typestate verification. Technical report, Tel Aviv University, 2007. www.cs.tau.ac.il/∼gretay.

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