Abstraction and Learning for Infinite-State Compositional Verification

Dimitra Giannakopoulou
NASA Ames
Moffett Field, CA, USA
dimitra.giannakopoulou@nasa.gov

Corina S. Păsăreanu
CMU/NASA Ames
Moffett Field, CA, USA
corina.s.pasareanu@nasa.gov

Despite many advances that enable the application of model checking techniques to the verification of large systems, the state-explosion problem remains the main challenge for scalability. Compositional verification addresses this challenge by decomposing the verification of a large system into the verification of its components. Recent techniques use learning-based approaches to automate compositional verification based on the assume-guarantee style reasoning. However, these techniques are only applicable to finite-state systems. In this work, we propose a new framework that interleaves abstraction and learning to perform automated compositional verification of infinite-state systems. We also discuss the role of learning and abstraction in the related context of interface generation for infinite-state components.

1 Introduction

Despite several breakthroughs that enable the application of model checking to the verification of realistic systems, the essential challenge in model checking remains the well-known state-space explosion problem: the size of a concurrent reactive system to be verified is the product of the sizes of its constituent components. Thus the cost of exhaustive verification as done in model checking grows exponentially in the number of state variables.

Compositional techniques attempt to tame this problem by applying verification to individual components and merging the results without analyzing the whole system. In checking components individually, it is often necessary to incorporate some knowledge of the context in which each component is expected to operate correctly. Assume-guarantee reasoning [21, 25] addresses this issue by using *assumptions* that capture the expectations that a component makes about its environment. The simplest such rule checks if a system composed of components M_1 and M_2 satisfies a property P by checking that M_1 under assumption A satisfies P (*Premise 1*) and discharging A on the environment M_2 (*Premise 2*). For safety properties, *Premise 2* amounts to checking that A is a conservative abstraction of M_2, *i.e.*, an abstraction that preserves all of M_2's execution paths. This rule is also represented as follows, where the notation is described in more detail in Section 2.

$$\frac{\begin{array}{ll} 1: & \langle A \rangle\ M_1\ \langle P \rangle \\ 2: & \langle true \rangle\ M_2\ \langle A \rangle \end{array}}{\langle true \rangle\ M_1 \parallel M_2\ \langle P \rangle}$$

Assumptions have traditionally been developed manually, a limiting factor to the practical impact of assume-guarantee reasoning. In this article, we review learning-based frameworks that automate the application of assume-guarantee reasoning [8, 28]. These frameworks use the L* automata learning algorithm [2] to generate and refine assumptions, based on results obtained from model checking individual components separately. Other related approaches followed (see e.g. articles in journal issue [14]).

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These prior approaches were performed in the context of *finite-state* components. In contrast, the focus of the present work is on compositional verification in the context of *infinite-state* (or very large) components, where the verification of individual components itself is intractable. We introduce component abstractions for this task, and explain how component abstraction refinement interacts with assumption generation. This article contributes a framework for automated assume-guarantee reasoning of infinite-state systems. A related problem that we studied in the past in the context of infinite-state systems is component interface generation [30]. We explain here the differences between the two approaches, in particular the different types of abstractions that are needed in each.

2 Formalisms

2.1 Component Models and Properties

2.1.1 Communicating State Machines

We model software components as (possibly infinite) communicating state machines. Note that typically components have implicit finite representations (e.g. a program) and only their semantics are given as infinite state machines.

Let $\mathscr{A}ct$ be the universal set of observable actions and let τ denote a local action *unobservable* to a component's environment.

A CSM M is a four-tuple $\langle Q, \alpha M, \delta, q_0 \rangle$ where:

- Q is a non-empty set of states.
- $\alpha M \subseteq \mathscr{A}ct$ is a set of observable actions called the *alphabet* of M.
- $\delta \subseteq Q \times (\alpha M \cup \{\tau\}) \times Q$ is a transition relation
- $q_0 \in Q$ is the initial state

We write $q \xrightarrow{a} q'$ for $(q,a,q') \in \delta$. A *trace* t of a CSM M is a finite sequence of observable actions that label the transitions that M can perform starting at its initial state (ignoring the τ-transitions). The *language* of M, denoted $\mathscr{L}(M)$ is the set of all traces of M.

Note that we assume that the state set Q may be infinite but the alphabet αM is finite; the actions in the alphabet can be seen as modeling e.g. sending and receiving of messages or method calls and returns for software components. Method parameters are not treated here (see [3, 16] for approaches that handle parameters).

We sometimes abuse the notation and denote by t both a trace and its trace CSM. For a trace t of length n, its trace CSM consists of $n+1$ states, where there is a transition between states m and $m+1$ on the m^{th} action in the trace t. For $\Sigma \subseteq \mathscr{A}ct$, we use $t \uparrow \Sigma$ to denote the trace obtained by removing from t all occurrences of actions $a \notin \Sigma$. Furthermore, $M \uparrow \Sigma$ is defined to be a CSM over alphabet Σ which is obtained from M by renaming to τ all the transitions labeled with actions that are not in Σ. Let t, t' be two traces and Σ, Σ' be the sets of actions occurring in t, t', respectively. By the *symmetric difference* of t and t' we mean the symmetric difference of the sets Σ and Σ'.

A CSM $M = \langle Q, \alpha M, \delta, q_0 \rangle$ is *non-deterministic* if any of these two conditions holds: 1) it contains τ-transitions or 2) if there exists $(q,a,q'),(q,a,q'') \in \delta$ such that $q' \neq q''$. Otherwise, M is *deterministic*.

2.1.2 Parallel Composition of CSMs

Let $M_1 = \langle Q^1, \alpha M_1, \delta^1, q_0^1 \rangle$ and $M_2 = \langle Q^2, \alpha M_2, \delta^2, q_0^2 \rangle$ be two CSMs. The parallel composition operator $\parallel$ is a commutative and associative operator that combines the behavior of two components by synchronizing the actions common to their alphabets and interleaving the remaining actions. Formally, $M_1 \parallel M_2$ is a CSM $M = \langle Q, \alpha M, \delta, q_0 \rangle$, where $Q = Q^1 \times Q^2$, $q_0 = (q_0^1, q_0^2)$, $\alpha M = \alpha M_1 \cup \alpha M_2$, and δ is defined as follows, where $q_1, q_1' \in Q^1$ and $q_2, q_2' \in Q^2$:

$$\frac{q_1 \xrightarrow{a} q_1',\ a \notin \alpha M_2}{(q_1, q_2) \xrightarrow{a} (q_1', q_2)} \qquad \frac{q_2 \xrightarrow{a} q_2',\ a \notin \alpha M_1}{(q_1, q_2) \xrightarrow{a} (q_1, q_2')}$$

$$\frac{q_1 \xrightarrow{a} q_1',\ q_2 \xrightarrow{a} q_2',\ a \neq \tau}{(q_1, q_2) \xrightarrow{a} (q_1', q_2')}$$

The language of $M_1 \parallel M_2$ is $\mathscr{L}(M_1 \parallel M_2) = \{t \mid t \uparrow \alpha M_1 \in \mathscr{L}(M_1) \wedge t \uparrow \alpha M_2 \in \mathscr{L}(M_2) \wedge t \in (\alpha M_1 \cup \alpha M_2)^*\}$

2.1.3 Properties

In this paper, we address assume-guarantee reasoning in the context of checking safety properties. For the context of our presentation, a safety property is modeled as a deterministic CSM P, whose language $\mathscr{L}(P)$ defines the set of acceptable behaviors over αP. For CSMs M and P where $\alpha P \subseteq \alpha M$, $M \models P$ if and only if

$$\forall t \in \mathscr{L}(M) : t \uparrow \alpha P \in \mathscr{L}(P).$$

Checking properties reduces to reachability checks: $M \models P$ holds iff a special error state is unreachable in $M \parallel P_{err}$, where P_{err} is the complement of P and is obtained by completing P such that each missing transition on αP becomes a transition to the error state.

2.2 Assume-guarantee Reasoning

In the assume-guarantee paradigm a formula is a triple $\langle A \rangle\ M\ \langle P \rangle$, where M is a component, P is a property, and A is an assumption about M's environment. The formula is true if whenever M is part of a system satisfying A, then the system must also guarantee P, *i.e.*, $\forall E$, $E \parallel M \models A$ implies $E \parallel M \models P$. Note that when $\alpha P \subseteq \alpha A \cup \alpha M$, this is equivalent to $A \parallel M \models P$.

Let M be a finite-state component with Σ being the set of its interaction points with the environment, i.e. the set of actions which will participate in the composition of M with another component from the environment. Furthermore, let P be a safety property. Then there is a natural notion of the *weakest assumption* A_w for M with respect to P, with $\alpha A_w = \Sigma$. A_w is characterized by two properties:

- *Safety:* $\langle A_w \rangle\ M\ \langle P \rangle$ holds.
- *Permisiveness:* A_w characterizes all the possible environments E under which P holds, *i.e.*$\forall E : M \parallel E \models P \Rightarrow E \models A_w$.

These two conditions essentially ensure that $\forall E : M \parallel E \models P$ iff $E \models A_w$. It has been shown that, for any finite-state component M, the weakest assumption A_w exists, and can be constructed algorithmically. The weakest assumption is associated with a similar notion of precision defined in the literature for "temporal" component interfaces [20], *i.e.*, interfaces that capture ordering relationships between invocations

of component methods. For example, an interface may describe the fact that closing a file before opening it is undesirable because an exception will be thrown. An ideal interface should precisely represent the component in all its intended usages. It should be *safe*, meaning that it should exclude all problematic interactions, and *permissive*, in that it should include all the good interactions [20].

Similarly, assumption safety is concerned with restricting behaviors to only those that satisfy P. Permissiveness is concerned with including behaviors, making sure that behaviors are restricted only if necessary. Permissiveness is desirable, because A_w is then appropriate for deciding whether an environment E is suitable for M_1 (if E does not satisfy A_w, then $E \parallel M_1$ does not satisfy P).

The simplest assume-guarantee rule is for checking a safety property P on a system with two components M_1 and M_2.

Rule ASYM

$$\frac{\begin{array}{ll} 1: & \langle A \rangle\ M_1\ \langle P \rangle \\ 2: & \langle true \rangle\ M_2\ \langle A \rangle \end{array}}{\langle true \rangle\ M_1 \parallel M_2\ \langle P \rangle}$$

In this rule, A denotes an assumption about the environment of M_1. Note that the rule is not symmetric in its use of the two components, and does not support circular reasoning. Despite its simplicity, experience has shown it to be quite useful in the context of checking safety properties.

2.2.1 Soundness and Completeness

Soundness of an assume-guarantee rule means that whenever its premises hold, its conclusion holds as well. Without soundness, we cannot rely on the correctness of conclusions reached by applications of the rule, making the rule useless for verification. Completeness states that whenever the conclusion of the rule is correct, the rule is applicable, i.e., there exist suitable assumptions such that the premises of the rule hold. Completeness is not needed to ensure correctness, but it is an important measure for the usability of the rule. Rule ASYM is both sound and complete. To show soundness, note that $\langle true \rangle\ M_2\ \langle A \rangle$ implies $\langle true \rangle\ M_1 \parallel M_2\ \langle A \rangle$. Then, since $\langle A \rangle\ M_1\ \langle P \rangle$ also holds, it follows that $\langle true \rangle\ M_1 \parallel M_2\ \langle P \rangle$ holds as well (from the definition of assume-guarantee triples). Completeness holds trivially, by substituting M_2 for A.

For the use of rule ASYM to be justified, the assumption should be (much) smaller than M_2, but still reflect M_2's behavior, i.e. A should be an abstraction of M_2, according to premise 2. Additionally, an appropriate assumption for the rule needs to "restrict" M_1 enough to satisfy P in premise 1. Coming up with such assumptions manually is highly non-trivial. In the next sections we describe techniques for synthesizing assumptions automatically.

2.3 Abstraction

To check properties of infinite-state components, we build *may* and *must* abstractions of software components. A popular technique uses predicate abstraction – a special instance of abstract interpretation [10] that maps a potentially infinite state transition system into a finite state transition system via a finite set of predicates $\mathsf{Preds} = \{p_1, \ldots, p_n\}$ over a program's variables.

An abstraction function α maps a concrete state q to a set of predicates that hold in q: $\alpha(q) = \{p \in \mathsf{Preds} \mid q \models p\}$. For a concrete transition we define corresponding *may* and *must* transitions. Let q_A, q'_A denote abstract states, and q, q' denote concrete states (in the un-abstracted system):

- $q_A \xrightarrow{a}_{must} q'_A$ iff $\forall q$ s.t. $\alpha(q) = q_A$, $\exists q'$ s.t. $\alpha(q') = q'_A$ and $q \xrightarrow{a} q'$.
- $q_A \xrightarrow{a}_{may} q'_A$ iff $\exists q$ s.t. $\alpha(q) = q_A$ and $\exists q'$ such that $\alpha(q') = q'_A$ and $q \xrightarrow{a} q'$.

Given component with communicating state machine C, the must and may abstractions with respect to the set of abstract predicates Preds are defined as $C^{must}_{\mathsf{Preds}} = (2^{\mathsf{Preds}}, \Sigma, \alpha(q_0), \longrightarrow_{must})$ and $C^{may}_{\mathsf{Preds}} = (2^{\mathsf{Preds}}, \Sigma, \alpha(q_0), \longrightarrow_{may})$, respectively. We write C^{must} or C^{may} when Preds is clear from the context.

The *must* abstraction consists of behaviors which are guaranteed to be present in the concrete (unabstracted) component; it represents an under-approximation as it might miss some concrete behaviors. The *may* abstraction represents an over-approximation; it consists of all concrete behaviors of the concrete component but it may also contain additional, spurious ones.

Algorithms for computing may and must abstractions with the help of a theorem prover are given in e.g. [26]. For automated abstraction refinement, we use weakest precondition calculations over counterexample traces [7, 23]. Let ϕ be a predicate characterizing a set of states. The weakest precondition of ϕ with respect to a transition τ_i is $wp(\phi, \tau_i) = \{q | (q \xrightarrow{\tau_i} q' \Longrightarrow \phi(q'))\}$ and it characterizes the largest set of states whose successors by transition τ_i satisfy ϕ.

From the above definitions it follows that the may and must abstractions define simulations between C^{must} and C, and between C and C^{may}, respectively. Since simulation implies trace inclusion, we have the following characterization of under- and over- approximations:

$$\mathscr{L}\left(C^{must}\right) \subseteq \mathscr{L}\left(C\right) \subseteq \mathscr{L}\left(C^{may}\right)$$

2.4 The L* Algorithm

L* was developed by Angluin [2] and later improved by Rivest and Schapire [29]. L* learns an unknown regular language U over alphabet Σ and produces a *minimal deterministic* finite state automaton (DFA) that accepts it. L* needs to interact with an oracle, called a *Minimally Adequate Teacher*, that answers two types of questions from L*. The first type is a *membership query* asking whether a string $\sigma \in \Sigma^*$ is in U. For the second type, the learning algorithm generates a *conjecture* A and asks whether $L(A) = U$. If $L(A) \neq U$ the Teacher returns a counterexample, which is a string σ in the symmetric difference of $L(A)$ and U. L* is guaranteed to terminate with a minimal automaton A for U. If A has n states, L* makes at most $n-1$ incorrect conjectures. The number of membership queries made by L* is $O(kn^2 + n\log m)$, where k is the size of Σ, n is the number of states in the minimal DFA for U, and m is the length of the longest counterexample returned when a conjecture is made.

3 Compositional Verification for Finite-State Systems

3.1 Learning Assumptions

From the definition of the weakest assumption A_w, one can observe that for A_w, the premises of Rule ASYM become necessary, in addition to being sufficient, for the conclusion of the rule to hold. In other words, $(\langle A_w \rangle\ M_1\ \langle P \rangle)$ and $(\langle true \rangle\ M_2\ \langle A \rangle_w)$ hold, if and only if $(\langle true \rangle\ M_1 \parallel M_2\ \langle P \rangle)$. This is an advantage for an automated assume-guarantee reasoning framework, since it enables us to also disprove properties of a system, compositionally.

The framework illustrated in Figure 1, and first presented in [8], provides a learning-based approach to assume-guarantee reasoning of finite-state components. In this framework, L* targets the computation of the weakest assumption A_w, and its application to rule ASYM. The set of communicating actions of

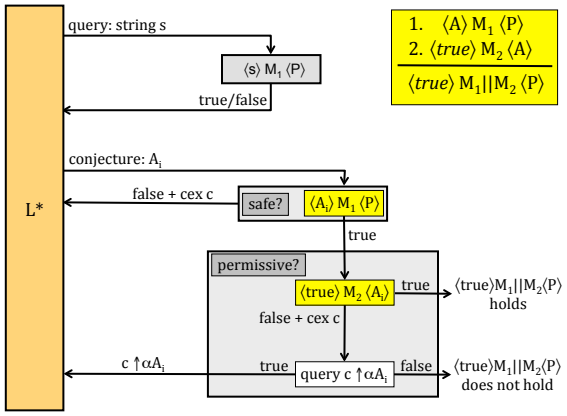

Figure 1: Learning Assumptions for Assume-Guarantee Reasoning

component M_1 with its environment is defined as: $(\alpha M_1 \cup \alpha P) \cap \alpha M_2$. We use this set as the alphabet of the weakest assumption in this context, hence the alphabet over which L* is learning. Note that the framework uses the knowledge of the actual environment of component M_1, namely, component M_2, to make the reasoning more efficient. More specifically, the framework implements a teacher for L*, meaning that it responds to queries and conjectures, as described in the following.

Queries. L* is first used to repeatedly *query* M_1 to check whether, in the context of strings s, M_1 violates the property. More formally, the query corresponds to checking the triple $\langle s \rangle\ M_1\ \langle P \rangle$ as illustrated in Figure 1. Checking $\langle s \rangle\ M_1\ \langle P \rangle$ corresponds to simulating string s on $M_1 \parallel P$: if an error is reachable, then the triple is *false*, otherwise it is *true*. The query returns *true/false* if $\langle s \rangle\ M_1\ \langle P \rangle$ is *true/false*, respectively. This is because, as mentioned, A_w allows all behaviors that satisfy the property, and disallows only violating behaviors.

Conjectures. The automaton A_i conjectured during iteration i, is checked for correctness, which in this context means checking whether it corresponds to the weakest assumption or not. As discussed earlier, the weakest assumption is safe and permissive. We therefore reduce equivalence queries to two separate checks, for safety, and permissiveness of A_i.

The first check is for safety: $\langle A_i \rangle\ M_1\ \langle P \rangle$; it can be performed by a model checker. If A_i is safe, then the teacher proceeds to checking permissiveness. If it is unsafe, the model checker returns a counterexample. The resulting counterexample c, projected on the assumption alphabet $\alpha A_i = \alpha A_w$, is returned to L* to refine its conjecture. The projection is necessary because L* needs counterexamples in terms of the alphabet over which it is learning.

As discussed, permissiveness is concerned with ensuring that the assumption does not exclude correct behaviors. However, given the fact that the main goal of the framework is to prove or disprove a property on the system using assume-guarantee reasoning, the framework does not need to generate a fully permissive assumption. Rather, it uses M_2 to add behaviors to over-restrictive assumptions on demand, and as needed for completion of the verification.

Note that the check for safety coincides with premise 1 of Rule ASYM. It therefore remains to check premise 2 ($\langle true \rangle\ M_2\ \langle A_i \rangle$). We use premise 2 to drive the permissiveness check and potentially complete assume-guarantee reasoning in Figure 1 as follows. If $\langle true \rangle\ M_2\ \langle A_i \rangle$ is *true*, then we know that both premises of Rule ASYM hold, and therefore that P holds for $M_1 \parallel M_2$. If $\langle true \rangle\ M_2\ \langle A_i \rangle$ is *false*, the

Teacher performs some analysis to determine the underlying reason (see Figure 1). The Teacher performs a query (of the L* type) in order to determine whether the returned counterexample c, projected to the alphabet of the assumption, belongs to A_w, in which case L* needs to refine the assumption. If the query returns *true*, then A_i is not permissive, so $c \uparrow \alpha A_i$ is returned to L* for refinement of its guess. If, on the other hand, the answer is false, it means that c is a word that belongs to M_2, in the context of which M_1 violates the property P. As a consequence, $M_1 \parallel M_2$ does not satisfy the property P.

Each new assumption marks the beginning of the next iteration cycle. Notice that the answers that the framework provides to L* are always precise with respect to the targeted weakest assumption. However, the framework uses M_2 to select which missing words to include in the language of the assumption. The reason is that we restrict our reasoning to a specific context, rather than accounting for all possible contexts, as required for the computation of A_w. That means, of course, that the assumption obtained from this framework does not necessarily correspond to A_w. On the other hand, we remind the reader that the primary goal is to obtain conclusive results from the assume guarantee rule. As soon as we are able to prove or disprove the property in the system, we stop refining the learned assumption, since we have achieved our goal. The assumption computed with this framework will be smaller than, or in the worst case equal to A_w in terms of number of states, as guaranteed by the characteristics of L*. In the worst case, where A_w itself is computed, the framework is guaranteed to terminate, because A_w is both necessary and sufficient, and therefore the framework will prove or disprove the property during this iteration.

3.2 Correctness Arguments.

Framework correctness argument: The framework directly uses the assume-guarantee rule Rule ASYM to answer conjectures. Soundness of the rule guarantees correctness of the positive answers by the framework. On the other hand, each counterexample reported is a real counterexample, as discussed above.

Teacher correctness argument: Correctness of the teacher corresponds to showing that all the answers returned to L* are consistent with A_w. This was discussed during the presentation of the framework above.

Termination argument: Since the Teacher implemented in our framework only comes back to L* for refinement with counterexamples related to A_w, the framework eventually converges to A_w, unless it terminates earlier. As discussed, A_w makes Rule ASYM sound and complete, and therefore our framework will return a conclusive answer at that iteration.

3.3 Extensions

The framework has been extended to reasoning about more than two components (by applying the framework recursively for Premise 2) and to other circular and symmetric rules [28]. It has been demonstrated on checking flight software models, where it achieved significant savings in terms of time and memory, and in some cases it was able to terminate while the monolithic (non-compositional) verification ran out of time and memory resources.

4 Compositional Verification for Infinite-State Systems

When reasoning about infinite-state components, abstractions need to be used to further reduce the state spaces of individual components. Figure 2 illustrates a learning-based framework for automating com-

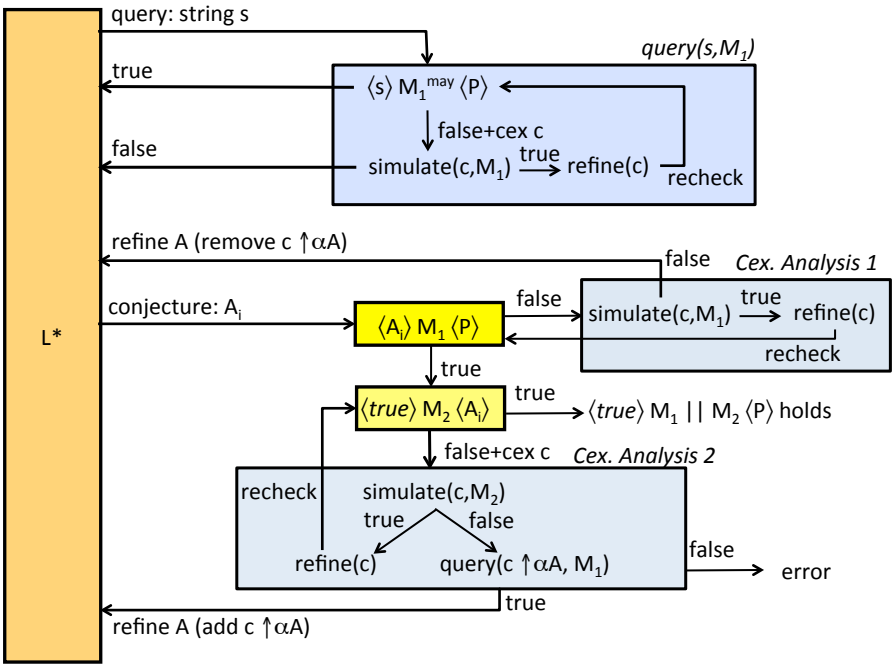

Figure 2: Automated Compositional Verification for Infinite-State Systems

positional verification for infinite-state systems.

In this section, we will first present how assume-guarantee reasoning of infinite-state components can be performed given some assumption A. We will subsequently discuss how such steps are introduced in creating automated assume-guarantee frameworks using learning for assumption inference.

$$\frac{\begin{array}{ll} 1: & \langle A \rangle\ M_1\ \langle P \rangle \\ 2: & \langle true \rangle\ M_2\ \langle A \rangle \end{array}}{\langle true \rangle\ M_1 \parallel M_2\ \langle P \rangle}$$

Going back to rule ASYM, let us assume that both M_1 and M_2 are infinite-state, or too large to perform the steps involved in the two premises by model checking. A standard approach used in such cases is to use abstractions of components M_1 and M_2.

As discussed in Section 2, finite over-approximations, or *may* abstractions, of a component, are typically used to guarantee correctness with respect to some property. May abstractions have more behavior than the system that they abstract. As such, counterexamples that are detected using may abstractions may be spurious. On the other hand, finite under-approximations, or *must* abstractions, are better suited for detecting property violations that are not spurious. Assume-guarantee rules allow us to infer correctness of a system based on local correctness checks of the system components. In this setting, it makes sense to use may abstractions of components M_1 and M_2, since $\langle A \rangle\ M_1^{may}\ \langle P \rangle \Longrightarrow \langle A \rangle\ M_1\ \langle P \rangle$ and $\langle true \rangle\ M_2^{may}\ \langle A \rangle \Longrightarrow \langle true \rangle\ M_2\ \langle A \rangle$.

We can therefore use the *may* abstractions to check the two premises of the assume-guarantee rule. If both premises hold for the may abstraction it follows that the premises hold for the original un-abstracted components, and hence P holds on the composition $M_1 \parallel M_2$. Let us now analyze the two premises given M_1^{may} and M_2^{may}.

- *Premise 1:* If $\langle A \rangle\ M_1^{may}\ \langle P \rangle$ holds, then we know that $\langle A \rangle\ M_1\ \langle P \rangle$ holds, which completes this check. If $\langle A \rangle\ M_1^{may}\ \langle P \rangle$ does not hold, then we obtain a counterexample, say c. This counterexample may be spurious either due to abstraction or due to the approximation introduced by assumption inference. Similarly to a CEGAR approach, we can determine whether c is spurious due to abstraction by checking if it can be simulated to completion on the infinite component M_1, using an operation $simulate(c, M_1)$. Since c is finite, simulation is possible. If c is not a valid execution of M_1, it means that it is a spurious counterexample, due to abstraction. If it is a valid execution of M_1, then it means that premise 1 does not hold, and therefore A is too approximate to make premise 1 pass. Below we will describe a new learning framework that is able to use this information to automatically refine the abstraction M_1^{may} or the assumption A, respectively.
- *Premise 2:* If $\langle true \rangle\ M_2^{may}\ \langle A \rangle$ holds, then we know that $\langle true \rangle\ M_2\ \langle A \rangle$ holds, which completes this check. If $\langle true \rangle\ M_2^{may}\ \langle A \rangle$ does not hold, then we obtain a counterexample, say c, which needs to be analyzed. This time, c may be spurious due to the abstraction of M_1 *or* M_2; furthermore, c may be spurious due to the approximation in the assumption. We therefore simulate c on M_2, using operation $simulate(c, M_2)$. If c is not a valid execution of M_2, it means that it is a spurious due to abstraction in M_2, and abstraction-refinement is needed for M_2. If c is a valid execution of M_2, then it means that premise 2 does not hold, and this may be an indication of a real error or it may mean that the counterexample is spurious either due to abstraction of M_1 or to approximation in A. Below, we describe how the proposed learning framework uses this information to automatically refine the component abstractions or the assumption A, as needed.

4.1 Learning for Assumption Inference

Let us now revisit the learning framework for finite-state systems and see how it can be extended for infinite-state. As discussed, L* needs a teacher that can answer membership queries and conjectures.

- *Membership queries:* A membership query needs to check if a finite word s over the alphabet αA_w should be included in the language of A_w. Similar to the finite-state case (see Figure 1) we are interested in finding out whether in the context of s, M_1 violates P or not. We first check $\langle s \rangle\ M_1^{may}\ \langle P \rangle$. If it leads to no error, it means this is true for M_1 as well (since the abstraction is conservative) and *true* is returned to L*. If an error is detected, the reported counterexample c is checked to see if it corresponds to a real trace in M_1. This amounts to symbolically simulating c on M_1, denoted by $simulate(c, M_1)$. Since s is finite, c is finite too so the simulation is possible and will terminate. If the result of simulation is that this is a real trace, indicating a real error in M_1, *false* is returned to L*. However, if this is not a real error, the spurious counterexample c is used to refine M_1^{may} and the membership check is repeated. The abstraction-refinement denoted by $refine(c)$ is described in more detail below.

When L* produces an assumption A_i, then the new framework needs to check whether A_i can be used to complete the assume-guarantee reasoning of the system. In other words, it needs to check Premises 1 and 2. For these checks, the framework uses M_1^{may} and M_2^{may}, respectively, as described above.

When the safety check associated with premise 1 passes, then the framework proceeds with the permissiveness check involving M_2. If, however, a counterexample c is obtained, then c needs to be analyzed as described below (see Figure 2).

- *Counterexample Analysis 1:* If the result of $simulate(c, M_1)$ is that c is a violating execution of M_1 then A_i must be refined; $c \uparrow \alpha A_i$ is returned to L*, and L* will work on creating a new approxima-

tion of the assumption. If c is not violating in M_1 then M_1^{may} must be refined, using $refine(c)$ and the safety check is performed again with the new abstraction.

The permissiveness check consists of applying premise 2 using M_2^{may} as described above. If the check passes, we can conclude that $\langle true \rangle\ M_1 \parallel M_2\ \langle P \rangle$ holds. If not, we analyze the returned counterexample c as described below (see Figure 2).

- *Counterexample Analysis 2:* If the result of $simulate(c, M_2)$ shows that c is not a real counterexample, then M_2^{may} is refined using $refine(c)$, and the permissiveness check is repeated. If the result however indicates a real trace in M_2, then we must further analyze c to determine if it uncovers a real violation in the system or not.

  Similar to the finite-state case (Figure 1), this further analysis amounts to performing a query for $c \uparrow \alpha A_w$ on M_1. Note that in the infinite-state case, performing a query might result in further refinements for M_1 and corresponding subsequent checks for the new abstractions (as described in the query check above). If the result of the analysis is that the assumption needs to be refined, the counterexample $c \uparrow \alpha A_w$ is returned to L*, which will work on creating a new approximation for A, based on new membership queries and conjecture checks.

Note that this framework has an important characteristic: the information that is communicated to L* is always correct with respect to the concrete system. As a result, refinement of abstractions does not require for L* to restart learning.

In our proposed framework, abstraction refinement is applied whenever a violating trace t is discovered that belongs to a *may* abstraction (M_1^{may} or M_2^{may}) but not to the corresponding un-abstracted components (M_1 and M_2 respectively). Consequently t must contain a *may* transition that has no correspondence in the un-abstracted system. We use a simple strategy based on weakest precondition calculations [30] to compute new abstraction predicates that are guaranteed to eliminate the spurious transitions. Given a counterexample t as a sequence of transitions $\{\tau_1, \tau_2 ... \tau_n\}$ we compute refinement predicates $wp(true, t)$ by using weakest preconditions recursively based on the following definition $wp(\phi, t) = wp(wp(\phi, \tau_n), \{\tau_1, \tau_2 ... \tau_{n-1}\})$.

4.2 Correctness and Termination

We argue now the correctness and the termination for the proposed algorithms. Our framework returns true only if both $\langle A \rangle\ M_1^{may}\ \langle P \rangle$ and $\langle true \rangle\ M_2^{may}\ \langle A \rangle$ hold. Since the assume guarantee rule is sound, it follows that $\langle true \rangle\ M_1^{may} \parallel M_2^{may}\ \langle P \rangle$ holds, and since the *may* abstractions are over-approximations, it follows that $\langle true \rangle\ M_1^{may} \parallel M_2^{may}\ \langle P \rangle$ holds as well. On the other hand, if the framework reports an error, it finds a trace which is both a trace of M_2 and of M_1 and it leads to a violation of P, hence it is an error in $M_1 \parallel M_2$ as well.

For infinite-state components, the abstraction-refinement algorithm used in our proposed framework may not always terminate. However, from previous work on automatic abstraction refinement [23], we know that if a component M has a finite bisimulation quotient, then abstraction-refinement (based on weakest preconditions calculations) converges to that finite quotient. It follows that there is a refinement iteration bound i such that M^{may} is bisimilar to M (in our case the argument applies to M_1 and M_2). Since bisimulation implies trace equivalence it follows that $\mathscr{L}(M^{may}) = \mathscr{L}(M)$ at that bound. Once that bound is reached, no abstraction-refinement is performed, and the obtained counter-examples will either be returned to L* for assumption-refinement or they will be returned to the user as real errors, in which case the computation will terminate. By the correctness of L* we are guaranteed that it will eventually

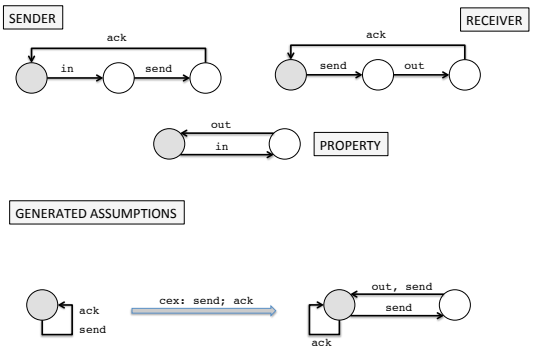

Figure 3: Learning-based AG reasoning for a finite system

produce A_w wrt. M_1^{may} and property P. During this step, checking premise 1 will return true (by definition of A_w) and checking premise 2 will either return true and terminate, or return a counterexample. This counterexample is a trace in $\mathscr{L}\left(M_2^{may}\right) = \mathscr{L}\left(M_2\right)$ that is not in $\mathscr{L}\left(A_w\right)$. Since A_w is both safe and permissive, counterexample analysis will return false and the framework will terminate.

The framework may terminate earlier, not necessarily when it reaches bisimulation quotients for M_1 and M_2, but as soon as the abstractions M_1^{may} and M_2^{may} and the inferred assumption A are good enough to show that the two premises hold or to expose a real counterexample.

5 Example: A simple communication protocol

In this section, we illustrate the presented algorithms through a very simple communication protocol. The protocol consists of two components, *Sender* and *Receiver*. We analyze two different versions of the protocol, one for the case where its components are finite-state, and one where they are infinite-state.

5.1 Finite State Protocol

The *Sender* and *Receiver* for the finite-state case are illustrated in Figure 3. The *Sender* starts by receiving input from the environment. It subsequently sends a message to the *Receiver*, and waits for an acknowledgement. The *Receiver*, upon a message being sent by the *Sender* produces an output, and subsequently acknowledges receipt of the message. The desired property from the environment's perspective is that actions *in* and *out* alternate, with *in* occurring first. As illustrated, the compositional verification framework produces two assumptions; the second assumption is suitable for completing the assume-guarantee reasoning for this example. Note that the assumption has 2 states, which is one state less than the *Receiver*. The example is small and used for illustrative purposes, so the benefits of compositional verification are modest.

5.2 Infinite State Protocol

Now let us modify the example with an infinite-state *Sender*. The *Sender* has a variable x, initially set to 0, and where x is in the domain of natural numbers. In Figure 4, we represent the component in terms

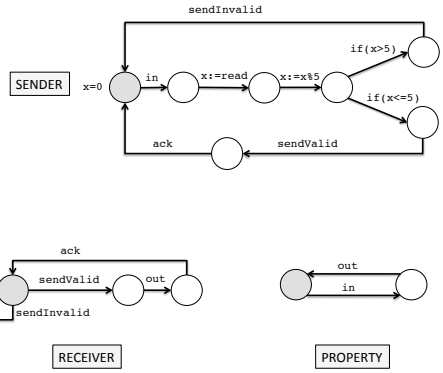

Figure 4: Infinite state communication protocol

of pseudo-code, displayed in terms of its control flow. Similarly to the finite-state case, the *Sender* starts by receiving input from the environment, which prompts it to perform a *read*, the results of which are stored in x. In other words, this represents the non-deterministic assignment of a natural number value to variable x, modeling in term the communication of a value from the environment. Subsequently, x is set to its previous value modulo 5. The control flow then branches depending on whether $x > 5$, in which case it communicates an invalid message, and otherwise it sends a valid message, and waits for an acknowledgement from the *Receiver*. The *Receiver* may now receive a valid message, in which case it behaves as in the finite-state case, but also an invalid message. In the latter case, it directly transits to its initial state and waits for the next message. The property is identical to the finite-state case.

Assume that one first creates an abstraction of *Sender* based on predicates $x = 0$ and $x > 0$. The abstraction is illustrated in Figure 5 whereas, Figure 6 depicts the learning process for this infinite state system. As illustrated in Figure 6 , when the learning algorithm queries the abstraction for *"sendInvalid"*, the answer to the query is negative. The detailed trace at the top of Figure 6 provides the exact trace of the abstracted sender that violates property *P*. However, if this trace is simulated on the concrete *Sender* component of Figure 4, we can detect that it is impossible for $(x > 5)$ to hold right after performing operation $(x := x\%5)$; therefore, this initial abstraction needs to be refined. If one adds predicates $x > 5$ and $x \leq 5$, then the learning framework is able to show that *P* is satisfied with assume guarantee reasoning. Note that the assumptions obtained are similar to the infinite-state case, where *send* is now split in two actions, *sendValid* and *sendInvalid*.

6 Interface Generation for Infinite-State Components

Assumptions are closely related to the notion of component interfaces. Intuitively, a component interface summarizes aspects of a component that are relevant to its customers. Traditionally, component interfaces have been of a purely syntactic form, that included information about the services/methods that can be invoked on the component, and their signatures, meaning the numbers and types of arguments and their return values. However, there is a recognized need for richer interfaces that capture additional, behavioral, aspects of a component.

Temporal interfaces, as introduced in Section 2, are richer interfaces that capture ordering relation-

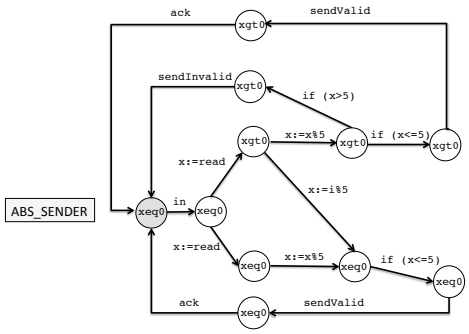

Figure 5: Abstracted sender - version 1

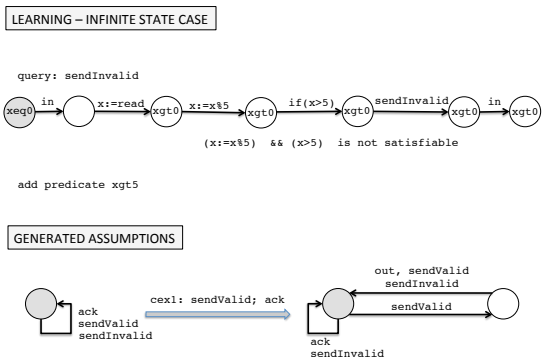

Figure 6: Learning-based AG reasoning for infinite system

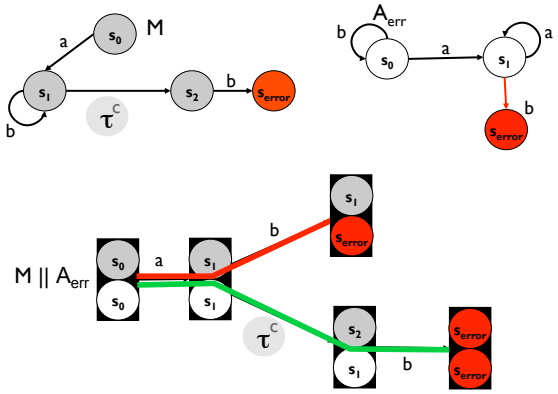

Figure 7: Checking for Permissiveness

ships between invocations of component methods. Ideally, a temporal interface should precisely represent the component in all its intended usages. In other words, it should include all the good interactions, and exclude all problematic interactions.

In such a context, component interfaces have the same flavor as assumptions that relate to safety properties, as studied in the previous section. However typically an interface summarizes the component *irrespective* of the environment in which the component is to be introduced, while we have seen that an assumption (used in compositional reasoning) serves as a potentially imprecise interface that is sufficient for breaking up a targeted verification problem into simpler problems; all components that participate in the verification problem are known and available.

In fact, a precise interface is similar to the weakest component assumption. It is therefore characterized in terms of two properties, safety, and permissiveness. For simplicity, we consider here error states that are not introduced by explicit properties, but are rather assumed to represent undesirable component states (e.g. assertion violations in the component's code). Interfaces can be learned through frameworks similar to those we developed for assume-guarantee reasoning; queries, and the part of conjectures related to safety, are answered in an identical way.

Permissiveness, however, is more difficult because the environment of the targeted component is not available. The example in Figure 7 shows how a permissiveness check could be performed. Component M has states named s_0, s_1, s_2, s_{error} and interface A has states named s_0, s_1 and s_{error}. A permissiveness check needs to detect sequences that are blocked by the interface but legal in the component. Such sequences identify that the interface is not permissive. This can be performed by checking reachability, in $M \parallel A$, of states of the form $[s_i, s_{error}]$, where $0 \leq i \leq 2$. According to this check, trace $\langle a, b \rangle$ leading to state $[s_1, s_{error}]$ in the composition could be an indication that A is not permissive. However this is not true, since the same sequence of actions leads to $[s_{error}, s_{error}]$ on a different path, due to non-determinism. This happens because the alphabet of the assumption is $\{a, b\}$, meaning that action c in M is considered as a τ from the point of view of A. In the figure, this is illustrated as a τ action covering action c.

This example illustrates the fact that non-determinism in component M may cause spurious counterexamples in the permissiveness reachability check described above. As a consequence, precise characterization of permissiveness requires determinization of component M, which can be performed using subset construction. The permissiveness check is therefore NP-hard [1], and can be inefficient in prac-

tice. Several approaches have been proposed to deal with this problem. Unless determinization is a viable solution for a targeted component M [3], heuristic approaches are often used to determine whether a counterexample is spurious [1, 15].

Let us examine now the case of infinite-state component M. Abstraction is again needed to reason about such components. However using *may* abstractions alone turns out to be insufficient, because the generated interfaces may be overly restricting (due to the spurious error traces present in the abstraction). In previous work [30], we have shown the following result:

Assume a component M, a may *abstraction* M^{may} *and a* must *abstraction* M^{must} *for M. If an interface A for M is* safe *with respect to* M^{may} *and* permissive *with respect to* M^{must}*, then A is safe and permissive with respect to M.*

Based on this result, we developed a framework [30] that interleaves abstraction-refinement and L* learning for the automated generation of interfaces for infinite-state components. The framework uses both M^{may} and M^{must} to compute an interface for M that is both safe and permissive. The abstractions are refined automatically from counterexamples obtained during the reachability checks performed by the framework.

It is interesting to note that in case component M is *observationally* deterministic (i.e. deterministic with respect to its interface actions), the *must* abstraction is deterministic as well. Thus its use enables us to avoid the exponentially expensive determinization step that is required when working with non-deterministic components. The idea of the framework, based on the result above, is to use M^{may} for the safety check, and M^{must} for the permissiveness check.

The safety check is similar to the compositional verification framework. Let us therefore analyze how the permissiveness check is performed with M^{must}, when M is observationally deterministic. If in $M^{must} \parallel A$ it is not possible to reach an error state in A that is an accepting state in M^{must}, then it means that A permissive, in which case the framework produces A as a safe and permissive interface for M. If, however, such a combined state is reachable by some counterexample c, then c is analyzed as follows. If c leads to an error state in M, then M^{must} needs to be refined to avoid this discrepancy. Otherwise, c represents a real counterexample to the permissiveness of A and it is returned to L* for refining the assumption. If, on the other hand, M^{must} is observationally non-deterministic, it must be determinized prior to performing the test.

In conclusion, we use both may and must abstractions for interface generation of infinite state components. In contrast, may abstractions are sufficient for compositional verification, because component M_2 is known and can be used for selective permissiveness checks.

7 Related Approaches

We briefly describe here some of the related work that combines abstraction and compositional reasoning in the context of infinite system analysis. The Magic tool performs verification of concurrent, message-passing C programs using abstraction-refinement in a compositional way; the work has been extended with a two-level abstraction scheme, but it does not use assume-guarantee style verification. The Blast tool uses predicate abstraction and has been extended to perform assume-guarantee reasoning for checking race conditions in multi-threaded C code [19]. In contrast to our work, it targets shared memory communicating programs, and therefore it uses a different style of assume guarantee rule. Moreover, the approach used by Blast is not based on learning. Bandera [9, 27] was aimed at verifying concurrent Java

programs. Bandera employed data abstraction and modular reasoning with user-supplied assumptions, but not automated assumption generation and CEGAR, as we do here. As already mentioned, algorithms for interface synthesis for infinite state components have been presented in [1, 3, 30]. Recently, L* learning has been combined with symbolic execution to automatically generate interfaces for Java classes that include methods with parameters [16].

8 Conclusion

In this paper, we discussed the different types of abstractions that can be used for applying learning-based assume-guarantee reasoning and interface generation to infinite-state systems. We proposed a new framework for automated compositional verification, and illustrated it with a simple example. At the present time, we are not able to perform extensive experimental evaluation of the framework. For the presented example, we carried out all steps, except for abstraction refinement, automatically. In the future, we plan to implement and evaluate extensively the proposed framework. We are also interested in evaluating the quality of the obtained abstractions and assumptions, and the efficiency of our interleaved approach.

Acknowledgment

Corina Păsăreanu uses this occasion to remember the wonderful times she spent at Kansas State University during her graduate studies. She would like to thank Dave Schmidt and the other professors in the Department of Computing and Information Sciences for having started her interest in abstraction and compositional reasoning, which have been the subject of her thesis and a recurrent research theme in her work since then.

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