

Loop Invariant Generation through Active Learning

Jiaying Li, Li Li, Le Guang Loc, Jun Sun

Singapore University of Technology and Design
jiaying_li@mymail.sutd.edu.sg
{li_li, guangloc_le, sunjun}@sutd.edu.sg

Abstract. Loop invariant generation is one of the fundamental problems in program analysis and verification. In this work, we propose an automatic generation method for inductive loop invariants through iterations of runtime sampling, machine learning and constraint solving. In each iteration, our method first collects real data at runtime based on selective sampling. Then, based on their satisfaction of the assumptions and assertions in the program, our method uses support vector machine to learn a loop invariant candidate, i.e., a conjunction of linear and polynomial constraints. Finally, if the candidate can be verified as the inductive loop invariant of the program, our method returns it directly and ends the generation process. Otherwise, the counter-example is used to refine the data sampling in the next iteration. The experiment evaluation shows that our method can be used to learn loop invariants effectively and automatically that cannot be learned by other loop invariant generation tools.

1 Introduction

In this work, we propose a method and a tool called ZILU for automatically learning loop invariants. ZILU works through an iterative process combining sampling, active learning and verification.

2 Problem Definition and Solution Overview

In the following, we assume that a program contains a finite set of integer variable $\{x, y, z, \dots\}$ and thus a program state is a valuation of the variables. A predicate on the variables is viewed as the maximum set of program states which satisfies the predicate. We use predicates and sets of program states interchangeably. Without loss of generality, we assume the input to ZILU is a Hoare triple

$$\begin{array}{l} \{Pre\} \\ while\ (Cond)\{ \\ \quad Body \\ \} \\ \{Post\} \end{array}$$

where *Pre* is the pre-condition, which should be satisfied before entering the loop; *Cond* is the loop guard condition, which is the only way to enter or exit the loop; *Body* is

```

void ex1 (int x) {
    int y = 355;
    if (x > 46) x = 46;
    while (x <= 100) {
        if (x >= 46) {
            y = y+1;
        }
        x = x + 1;
    }
    assert (y==409);
}

```

Fig. 1. An example adopted from [?]

```

void ex2 () {
    lock=0;new=old+1;
    while (new!=old) {
        lock=1;old=new;
        if (foo(new)) {
            lock=0;new++;
        }
    }
    if (lock==0)
        error();
}

```

Fig. 2. An example adopted from [?]

the loop body, in which we assume there is no *break* or *goto* statement which can jump out of the loop without checking *cond*; and *Post* is the post-condition, which should be satisfied after the loop.

For simplicity, we assume that *Body* is a function such that $Body(s) = s'$ means that starting at a program state s , executing *Body* would result in a program state s' . Furthermore, we write $Body(Pr)$ where Pr to denote the set $\{s' \mid \exists s \in Pr : Body(s) = s'\}$. The goal is thus to automatically obtain a loop invariant such that the following conditions are satisfied.

$$\begin{aligned}
 Pre &\Rightarrow Inv & (1) \\
 Inv &\Rightarrow Body(Inv \wedge Cond) & (2) \\
 Inv \wedge \neg Cond &\Rightarrow Post & (3)
 \end{aligned}$$

Example 1. We use the two examples shown in Figure 1 and 2 to illustrate how our approach works. In *ex1*, the precondition of the loop is $y = 355 \wedge x \leq 46$ and the post-condition is $y = 409$. In *ex2*, the precondition is that $lock = 0 \wedge new = old + 1$ and the post-condition (necessary so that there is no error) is $lock = 1$. We remark that $foo(new)$ is an external function which *deterministically* returns either true or false, i.e., it returns true if *new* is even; otherwise, it returns false. We will discuss in Section how our approach would work if $foo(new)$ is non-deterministic.

Problem Definition In this work, we assume that given the Hoare triple, there is either a counterexample (i.e., a program state s such that $s \in Pre$ and executing the program from s results in failing *post*) or there exists an invariant satisfying (1) and (2) and (3). Furthermore, the invariant *inv* is a boolean formula over a linear inequality constraint of the form $ax + bx + \dots \geq d$ where a, b, d are bounded integer constants; and *inv* contains no more than k such statements. We remark that such invariant is in general not convex and thus existing approaches on learning convex invariants do not work [].

Overview of Our Approach Our approach to solve the problem is illustrated in Figure ???. Firstly, we randomly generate a set of program states right before the loop and test the program. Based on the testing results, we obtain program states which must or must not satisfy any invariant satisfying (1), (2) and (3). Secondly, we develop an algorithm for generating candidate invariants based classification techniques from the

machine learning community. Thirdly, to overcome the limitation of the sampled program states, we adopt active learning techniques, in particular, selective sampling, to refine the candidate invariants. Lastly, we rely on constraint solving techniques to check whether the generate invariant satisfies (1) and (2) and (3). If it does, we report that our approach is successful; otherwise, using the counterexamples generated by the constraint solvers, we repeat from the second step. In this following sections, we present details of each step.

3 Labeling

In this step, we sample, either randomly or using tools based on the idea of concolic testing [], a set T of program states and test the program starting with each program state s in T . We write $Body^*(s)$ to denote the set of program states which could be reached after executing zero or more iterations of the loop starting from s . We write $Body^*(T)$ to denote $\{s' \mid \exists s \in T \cdot s' \in Body^*(s)\}$. Furthermore, we write $s \Rightarrow s'$ to denote that starting with a program state s would result in state s' when the loop terminates.

We categorize program states in $Body^*(T)$ into four sets: C_T which stands for counter-example trace, P_T which stands for traces with positive labels, N_T which stands for traces with negative labels and U_T which stands for traces with unknown labels. They can be judged by the following rules:

- Set C_T is $\{s \in Body^*(T) \mid s \in Pre \wedge s \Rightarrow s' \wedge s' \notin Post\}$;
- Set P_T is $\{s \in Body^*(T) \mid s \in Pre \wedge s \Rightarrow s' \wedge s' \in Post\}$;
- Set N_T is $\{s \in Body^*(T) \mid s \notin Pre \wedge s \Rightarrow s' \wedge s' \notin Post\}$;
- Set U_T is $\{s \in Body^*(T) \mid s \notin Pre \wedge s \Rightarrow s' \wedge s' \in Post\}$;

We remark that anytime a program state in C_T is identified, a counter-example is found and ZILU reports that verification is failed immediately. Otherwise, because Inv must satisfy (1),(2) and (3), we know that $P_T \subseteq Inv$ and $N_T \cap Inv = \emptyset$. The program states in U_T may or not may be in Inv . If we know that a program state $s \in U_T$ is in Inv , $Body^*(s) \subseteq Inv$.

Example 2.

4 Classification

After sampling, we obtain some program states must be in inv and some must not. Thus, any candidate invariant must be able to perfectly classify these states. We apply classification techniques from the machine learning community to obtain classifiers as candidate invariants.

In the following, we present how we obtain a classifier automatically using SVM. SVM is a supervised machine learning algorithm for classification and regression analysis. We use its binary classification functionality. Mathematically, the binary classification functionality of (linear) SVM works as follows. Given two sets of feature

vectors F^+ and F^- , it generates, if there is any, a linear constraint in the form of $ax + by + \dots \geq d$ where x and y are feature values and a, b, d are constants, such that every state $s \in F^+$ satisfies the constraint and every state $s' \in F^-$ fails the constraint. In this work, we always choose the *optimal margin classifier* (see the definition in [?]) if possible. This half space could be seen as the strongest witness why the two data states are different. In the following, we write $svm(F^+, F^-)$ to denote the function which returns a linear classifier

If, however, F^+ and F^- cannot be perfectly classified by one half space only, a more complicated function f must be adopted. For instance, if there is a classifier in the form of conjunctive of multiple half spaces, the algorithm presented in [?] can be used to identify such a classifier.

4.1 Clustering

Based on the above assumption, the linear constraints ϕ_i divide the space into at most 2^k convex regions. One simple example is shown in Figure ?? . All program states in the same region must have the same label, i.e., whether it satisfies the invariant or not. Every pair of regions R_1 and R_2 must be linearly separable, i.e., there exists some linear constraint ϕ such that $R_1 \subseteq \phi$ and $R_2 \cap \phi = \emptyset$. Based on this observation, a naive algorithm for clustering the states in F^+ and F^- would work as follows: given a k value such that $k \geq 2$, we randomly assign every state s in $F^+ \cup F^-$ to a region R_i as long as all states in the same region have the same label and every pair of regions remain linearly separable. We remark that if k is 2, there is only one clustering. In general, this algorithm is rather inefficient if you try all possible clustering. Intuitively, however, ‘nearby’ states often belong to the same clustering and thus in the following algorithm, we first group near-by states and then identify the clustering.

Algorithm 1 works in two phases. In the first phase we apply k-means algorithm [] to group the data into linearly separable clusters. Notice that the states in F^+ and F^- are clustered separably since all states in the same cluster must have the same label. In order to avoid too many clusters, in the second phase, we merge clusters into larger clusters.

Example 3.

Proposition 1. *cluster(F^+, F^-) returns two sets of clusters $\{R_1^+, R_2^+, \dots, R_m^+\}$ and $\{R_1^-, R_2^-, \dots, R_n^-\}$ such that every pair of R_i^+ and R_j^- where $1 \leq i \leq m$ and $1 \leq j \leq n$ is linearly separable.* \square

4.2 Classification

After the last step, we obtain the clusters $R_1^+, R_2^+, \dots, R_m^+$ and $R_1^-, R_2^-, \dots, R_n^-$ (where $m \leq k$ and $n \leq k$). Next, we generate candidate classifiers. Our approach is based on the observation that for each actual classifier (i.e., a clause in *inv*), there exists at least one way of re-labeling the clusters such that the classifier would classify all states correctly. For instance, Figure ?? shows the states can be re-labeled so that a linear constraint in Figure ?? becomes a classifier for all states. Based on the observation, we design Algorithm 2 to identify candidate invariant.

Algorithm 1: Algorithm *cluster*

Input: F^+ and F^-
Output: a set of clusters which are pairwise linearly separable

```

1 let  $k = 1$ ;
2 while  $k < K$  do
3   apply  $k$ -means algorithm to cluster  $F^+$  into  $k$  clusters  $R_1^+, R_2^+, \dots, R_k^+$ ;
4   apply  $k$ -means algorithm to cluster  $F^-$  into  $k$  clusters  $R_1^-, R_2^-, \dots, R_k^-$ ;
5   if every pair of  $R_i^+$  and  $R_j^-$  where  $1 \leq i \leq k$  and  $1 \leq j \leq k$  is linearly separable then
6     break;
7    $k = k + 1$ ;
8 let merged be true;
9 while merged do
10  let merged be false;
11  for each pair  $R_i^+$  and  $R_j^+$  where  $i \neq j$  do
12    if  $R_i^+ \cup R_j^+$  is linearly separable from  $R_i^-$  for all  $i$  then
13      merge  $R_i^+$  and  $R_j^+$ ; set merged be true;
14  for each pair  $R_i^-$  and  $R_j^-$  where  $i \neq j$  do
15    if  $R_i^- \cup R_j^-$  is linearly separable from  $R_i^+$  for all  $i$  then
16      merge  $R_i^-$  and  $R_j^-$ ; set merged be true;
17 return the clusters;

```

Firstly, we identify a set X of candidate linear constraints. For each pair of clusters with different labels, for any possible re-labeling of the other clusters, if there is a linear classifier which perfectly classifies all states after relabeling, we add the linear classifier into X . Whenever any two clusters can be separated by a classifier in X , we return a candidate invariant based on X which is in the following form.

$$\begin{aligned}
& \bigwedge \{ \phi \in X \mid R_1^+ \subseteq \phi \} \vee \\
& \bigwedge \{ \phi \in X \mid R_2^+ \subseteq \phi \} \vee \\
& \dots \\
& \bigwedge \{ \phi \in X \mid R_m^+ \subseteq \phi \}
\end{aligned}$$

In the worst case, the loop from line 2 to 8 would iteration for $m * n * 2^{m+n-2}$ times.

Example 4.

Proposition 2. Given two set of states F^+ and F^- such that there is a classifier in the assumed form, $\text{classify}(F^+, F^-)$ always returns a perfect classifier. \square

5 Selective Sampling

Due to the limited set of samples we have (which is often referred to as labeled samples in the machine learning community), the classifier obtained above might be far from

Algorithm 2: Algorithm *classify*

Input: clusters $R_1^+, R_2^+, \dots, R_m^+$ and $R_1^-, R_2^-, \dots, R_n^-$
Output: a candidate invariant

```

1 let  $X$  be an empty sequence;
2 for each pair  $R_i^+$  and  $R_j^-$  where  $1 \leq i \leq m$  and  $1 \leq j \leq n$  do
3   for each possible labeling of the clusters other than  $R_i^+$  and  $R_j^-$  do
4     apply SVM to generate a linear classifier;
5     if there is a perfect classifier  $inv$  then
6       add  $inv$  into  $X$ ;
7   if any two clusters with different labels can be separated by a classifier in  $X$  then
8     return the candidate invariant based on  $X$ ;

```

Algorithm 3: Algorithm *activeLearning*

Input: F^+ and F^-
Output: a classifier for F^+ and F^-

```

1 let  $old$  be null;
2 while true do
3   let  $f = \text{classify}(F^+, F^-)$ ;
4   if  $f$  is identical to  $old$  then
5     return  $f$ ;
6   let  $old = f$ ;
7   let  $sam$  be a set of samples computed by selective sampling;
8   test the program and update  $F^+$  and  $F^-$  accordingly;

```

being correct. In fact, without labeled samples which are right on the boundary of the ‘actual’ classifier, it is very unlikely that we would find it. Intuitively, in order to get the ‘actual’ classifier, we would require samples which would distinguish the actual one from any nearby one. This problem has been discussed and addressed in the machine learning community using active learning and selective sampling [?].

The concept of active learning or selective sampling refers to the approaches that aim at reducing the labeling effort by selecting only the most informative samples to be labeled. SVM selective sampling techniques have been proven effective in achieving a high accuracy with fewer examples in many applications [?,?]. The basic idea of selective sampling is that at each round, we select the samples that are the closest to the classification boundary so that they are the most difficult to classify and the most informative to label. Since an SVM classification function is represented by support vectors which are the samples closest to the boundary, this selective sampling effectively learns an accurate function with fewer labeled data [?]. In our setting, this means that we should sample a program state right by the classifier and test the program with that state to label that feature vector so that the classifier would be improved.

Algorithm 3 presents details on how active learning is implemented in ZILU. At line 2, we obtain a classifier based on Algorithm 2. We compare the newly obtained classifier

Algorithm 4: Algorithm *overall***Input:** *Pre, Cond, Body, Post***Output:** an invariant which completes the proof or a counterexample

```

1  let  $T$  be a set of random samples;
2  while true do
3    test the program for each sample in  $T$ ;
4    if a state  $s$  in  $CT$  is identified then
5      return  $s$  as a counterexample;
6    let  $P, N$  and  $NP$  be the respective sets accordingly;
7    let  $Inv_u = \text{activeLearning}(P, N \cup NP)$ ;
8    let  $Inv_o = \text{activeLearning}(P \cup NP, N)$ ;
9    let  $Inv_s = \text{activeLearning}(P, N)$ ;
10   for each  $Inv$  in  $\{Inv_u, Inv_o, Inv_s\}$  do
11     if (1) or (2) or (3) is not satisfied then
12       add the counterexample into  $T$ ;
13     else
14       return  $Inv$  as the proof;

```

with the previous one at line 4, if they are identical, we return the classifier; otherwise we apply selective sampling so that we can generate additional labeled samples for improving the classifier. In particular, at line 5, we apply standard techniques [?] to select the most informative sample. Notice that in our setting, the most informative samples are those which are exactly on the lines and therefore can be obtained by solving an equation system. At line 8, we test the program with the newly generated samples so as to label them accordingly.

Example 5.

Proposition 3. Algorithm *activeLearning* always eventually terminates. \square

6 Verification

Given a learned predicate Inv , we verify whether constraint (1), (2) and (3) are satisfied using symbolic execution. If all of them are satisfied, we successfully verify the program. Otherwise, if any of them is violated, the counterexample obtained is added to the set of sample X , which is then tested, categorized, used for active learning accordingly. The overall algorithm is presented in Figure 4.

We remark that we learn three classifiers as candidates for the loop invariant: U , OU , O such that

- U classifies states in P and those in $N \cup NP$.
- O classifies states in N and those in $P \cup NP$.
- OU classifies states in P and N ;

Intuitively, U would be an under-approximation of Inv (by assuming states in NP does not satisfy Inv); O would be an over-approximation of Inv (by assuming states in NP does satisfy Inv); and OU would be an safe-approximation of Inv (by using states which we are certain whether they are in Inv or not).

Example 6.

Theorem 1. *Algorithm overall always eventually terminates and it is correct.* □

7 Implementation and Evaluation

8 Related Work

9 Conclusion

Limitation and Potential Remedies We remark that in theory, we could learn non-linear classifier using methods like SVM with kernel methods []. Nonetheless, due to the limitation of proving capability and tools with regards to non-linear constraints, we leave those to our future work. Furthermore, we assume there is a bound k on the number of clauses in the variant. In practice, we would expect (refer to empirical evidence in Section 7) often k is of a small value.

References