Abstraction Learning

Joxan Jaffar, Jorge Navas, and Andrew Santosa

National University of Singapore

A state-of-the-art approach for proving safe programs is *CounterExample-Guided Abstraction Refinement* (CEGAR) which performs a “abstraction-verification-refinement” cycle by starting with a coarse abstract model that is then refined repeatedly whenever a counterexample is encountered. In this work, we present a dual approach which starts with a concrete model of the program but progressively abstracts away details but only when these are known to be irrelevant. We call this concept *Abstraction Learning* (AL). In order to deal with loops, our algorithm is encapsulated in an iterative deepening search where, because of a particular depth bound, abstraction is forced upon loops. This abstraction will correspond to the strongest loop invariant we can discover. As in CEGAR, this abstraction is of a speculative nature: if the proof is unsuccessful, the abstraction is removed and we initiate a new attempt using a new depth bound.

A key difference between AL and CEGAR is that AL detects more *infeasible paths* in the state-space traversal phase. We argue that this key feature poses unique benefits, and demonstrate the performance of our prototype implementation against the state-of-the-art BLAST system.