Abstract Interpretation

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Overview

- Deductive verifiers require annotations (e.g., loop invariants) from user
- Fortunately, many techniques that can automatically learn loop invariants
- A common framework for this purpose is Abstract Interpretation (AI)
- Abstract interpretation forms the basis of most static analyzers

Key Idea: Over-approximation

- Abstract interpretation is a framework for computing over-approximations of program states
- Cannot reason about the exact program behavior due to undecidability (and also for scalability reasons)
- But we can obtain a conservative over-approximation and this can be enough to prove program correctness

Motivating Example

- What does this function do?
- Annotations computed automatically using an AI tool (Apron)

The AI Recipe

Abstract interpretation provides a recipe for computing over-approximations of program behavior

1. Define abstract domain – fixes “shape” of the invariants
   - e.g., \( c_1 \leq x \leq c_2 \) (intervals) or \( \pm x \pm y \leq c \) (octagons)

2. Define abstract semantics (transformers)
   - Define how to symbolically execute each statement in the chosen abstract domain
   - Must be sound wrt to concrete semantics

3. Iterate abstract transformers until fixed point
   - The fixed-point is an over-approximation of program behavior

Simple Example: Sign Domain

- Suppose we want to infer invariants of the form \( x \mathbin{\star} 0 \) where \( \mathbin{\star} \in \{\geq, =, >, <\} \) (i.e., zero, non-negative, positive, negative)
- This corresponds to the following abstract domain represented as lattice:

  - Lattice is a partially ordered set \((S, \sqsubseteq)\) where each pair of elements has a least upper bound or join (\(\sqcup\))

Concretization and Abstraction Functions

- The “meaning” of abstract domain is given by abstraction and concretization functions that relate concrete and abstract values.

- **Concretization function** \( \gamma \) maps each abstract value to sets of concrete elements:
  \[
  \gamma(\text{pos}) = \{ x \mid x \in \mathbb{Z} \land x > 0 \}
  \]

- **Abstraction function** \( \alpha \) maps sets of concrete elements to the most precise value in the abstract domain:
  \[
  \alpha(\{2, 10, 0\}) = \text{non-neg}
  \]
  \[
  \alpha(\{3, 99\}) = \text{pos}
  \]
  \[
  \alpha(\{-3, 2\}) = \top
  \]

Requirement: Galois Connection

- **Important requirement**: concrete domain \( D \) and abstract domain \( \hat{D} \) must be related through Galois connection:
  \[
  \forall x \in D, \forall \hat{x} \in \hat{D}. \alpha(x) \subseteq \hat{x} \Leftrightarrow x \subseteq \gamma(\hat{x})
  \]

  \[
  \begin{array}{cccccc}
  \text{pos} & \text{neg} & \text{zero} & \text{non-neg} & \top & \bot \\
  \text{pos} & \top & \text{pos} & \text{pos} & \top & \bot \\
  \text{neg} & \top & \text{neg} & \top & \bot & \bot \\
  \text{zero} & \text{pos} & \text{neg} & \text{zero} & \text{non-neg} & \top & \bot \\
  \text{non-neg} & \text{pos} & \top & \text{non-neg} & \text{non-neg} & \top & \bot \\
  \top & \top & \top & \top & \top & \bot & \bot \\
  \bot & \bot & \bot & \bot & \bot & \bot & \bot \\
  \end{array}
  \]

Back to Our Example

- For our sign analysis, we can define abstract transformer for \( x = y + z \) as follows:

\[
\begin{array}{ccccccc}
\text{pos} & \text{neg} & \text{zero} & \text{non-neg} & \top & \bot \\
\top & \text{pos} & \text{pos} & \text{pos} & \top & \bot \\
\top & \text{neg} & \text{neg} & \top & \bot & \bot \\
\text{zero} & \text{pos} & \text{neg} & \text{zero} & \text{non-neg} & \top & \bot \\
\text{non-neg} & \text{pos} & \top & \text{non-neg} & \text{non-neg} & \top & \bot \\
\top & \top & \top & \top & \top & \bot & \bot \\
\bot & \bot & \bot & \bot & \bot & \bot & \bot \\
\end{array}
\]

Soundness of Abstract Transformers

- **Important requirement**: Abstract semantics must be sound (i.e., faithfully models) the concrete semantics.

  - If \( F \) is the concrete transformer and \( \hat{F} \) is its abstract counterpart, soundness of \( \hat{F} \) means:
    \[
    \forall x \in D, \forall \hat{x} \in \hat{D}. \alpha(x) \subseteq \hat{x} \Rightarrow \hat{x} \subseteq \gamma(\hat{x})
    \]

- If \( \hat{x} \) is an overapproximation of \( x \), then \( \hat{F}(\hat{x}) \) is an over-approximation of \( F(x) \).
Fixed-point Computations

- **Fixed-point computation**: Repeated symbolic execution of the program using abstract semantics until our approximation of the program reaches an equilibrium:

  \[
  \bigcup_{k \in \mathbb{N}} F^k(\bot)
  \]

- **Least fixed-point**: Start with underapproximation and grow the approximation until it stops growing

- Assuming correctness of your abstract semantics, the least fixed point is an **overapproximation** of the program!

Performing Least Fixed Point Computation

- Represent program as a control-flow graph
- Want to compute abstract values at every program point
- Initialize all abstract states to \( \bot \)
- Repeat until no abstract state changes at any program point:
  - Compute abstract state on entry to a basic block \( B \) by taking the join of \( B \)'s predecessors
  - Symbolically execute each basic block using abstract semantics

An Example

\[
\begin{aligned}
x &= 0; \\
y &= 0; \\
\text{while} \ (x + y \leq n) \\
& \quad \{ \\
& \quad \quad \text{if} \ (z == 0) \\
& \quad \quad \quad x = x+1; \\
& \quad \quad \quad \text{else} \\
& \quad \quad \quad \quad y = y+1; \}
\end{aligned}
\]

Is \( x \) always non-negative inside the loop?

Termination of Fixed Point Computation

- In this example, we quickly reached least fixed point — but does this computation always terminate?
  - Yes if the lattice has finite height; otherwise, it might not
  - Unfortunately, many interesting domains do not have this property, so we need widening operators for convergence.

Interval Analysis

- In the interval domain, abstract values are of the form \([c_1, c_2]\)
  where \( c_1 \) is a lower bound and \( c_2 \) has an upper bound
- If the abstract value for \( x \) is \([1, 3]\) at some program point \( P \), this means \( 1 \leq x \leq 3 \) is an invariant of \( P \)

Interval Analysis

Does not have finite-height property!
Widening

- If abstract domain does not have this property, we need a **widening** \( \nabla \) operator that forces convergence

- Conditions on \( \nabla \):
  1. \( \forall a, b \in \mathbb{D}. \ a \sqcup b \sqsubseteq a\nabla b \)
  2. For all increasing chains \( d_0 \sqsubseteq d_1 \sqsubseteq \ldots \) the ascending chaining \( d_0 \sqsubseteq d_0^\nabla \sqsubseteq d_1^\nabla \sqsubseteq \ldots \) eventually stabilizes where \( d_0^\nabla = d_0 \) and \( d_{i+1} = d_i^\nabla \cap d_{i+1} \)

- Overapproximate ifp by using widening operator rather than join \( \Rightarrow \) sound and guaranteed to terminate

- This is called **post-fixed-point**

### Example with Widening

```
x = 5
y = 7
loop head
exit block
i = *
y = y + 1
i = i - 1
i >= 0
i < 0
```

```
x = 1
loop head
exit block
x = 2
```

固定点！

### Motivation for Narrowing

- In many cases, widening overshoots and generates imprecise results

- Consider this example:
  ```
  x = 1;
  while(*) {
    x = 2;
  }
  ```

- After widening, \( x \)'s abstract value will be \([1, \infty] \) after the loop; but more precise value is \([1, 2] \)

### Widening in Interval Domain

- For the interval domain, we can define the following simple widening operator:

  \[
  [a, b] \nabla \bot = [a, b] \\
  \bot \nabla [a, b] = [a, b] \\
  [a, b] \nabla [c, d] = \left( [a < c?a : d, b < d?b : b] \right)
  \]

\[
\begin{align*}
[1, 2] \nabla [0, 2] &= \\ [2, 3] \\
[0, 2] \nabla [1, 2] &= \\ [1, 5] \\
[1, 5] \nabla [1, 5] &= \\ [2, 4] \\
\end{align*}
\]

### Narrowing

- **Idea:** After finding a post-fixed-point (using widening), have a second pass using a **narrowing** operator

- Narrowing operator \( \triangle \) must satisfy the following conditions:
  1. \( \forall x, y \in \mathbb{D}. \ (y \sqsubseteq x) \Rightarrow y \sqsubseteq (x \triangle y) \sqsubseteq x \)
  2. For all decreasing chains \( y_0 \sqsupseteq y_1 \sqsupseteq \ldots \), the sequence \( y_0 = y_0, \ldots, y_{i+1} = y_i \triangle y_{i+1} \) converges

- For interval domain, we can define \( \triangle \) as follows:

\[
\begin{align*}
[a, b] \triangle \bot &= \bot \\
\bot \triangle [a, b] &= \bot \\
[a, b] \triangle [c, d] &= \left( [a = \infty?c : a, b = \infty?d : b] \right)
\end{align*}
\]

### Example with Narrowing

```
x = 1
loop head
exit block
x = 2
```

```
x = 1
loop head
exit block
x = 2
```

```
x = 1
loop head
exit block
x = 2
```

```
x = 1
loop head
exit block
x = 2
```

```
x = 1
loop head
exit block
x = 2
```
Relational Abstract Domains

- Both the sign and interval domain are non-relational domains (i.e., do not relate different program variables)
- Relational domains track relationships between variables and are more powerful
- A motivating example:
  
  ```
  x=0; y=0;
  while(*) {
    x = x+1; y = y+1;
  }
  assert(x=y);
  ```
  
  Cannot prove this assertion using interval domain

Examples of Relational Domains

- **Karr’s domain**: Tracks equalities between variables (e.g., \(x = 2y + z\))
- **Octagon domain**: Constraints of the form \(\pm x \pm y \leq c\)
- **Polyhedra domain**: Constraints of the form \(c_1x_1 + \ldots c_nx_n \leq c\)
  
  Polyhedra domain most precise among these, but can be expensive (exponential complexity)
- Octagons less precise but cubic time complexity

Message from Patrick Cousot

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Varieties of researchers in formal methods:
(i) explicitly use abstract interpretation and are happy to meet up and to discuss its applicability
(ii) implicitly use abstract interpretation and love it
(iii) pretend to use abstract interpretation, but misses it
(iv) don’t know that they use abstract interpretation, but would benefit from it
(v) never too late to upgrade.
```