

Abstract interpretation part 2: more of the same, plus widening

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15-8190: Program Analysis

Correctness holds when:

- The abstract domain lattice has finite height.
- The flow functions are monotonic.
- The abstraction function is correct.
 - Easy enough for zero analysis, at least.
- The flow functions are locally sound.
 - Explicit link to semantics!

Collecting Semantics

- Any state σ has type $\text{Var} \rightarrow \mathbb{Z}$, varies from program point to program point.
- Properly define program points as a set of **labels**
 - Now, we are answering questions about properties with respect to program points (e.g., is x always positive at label i ?)
- To answer these questions define *contexts*:
$$C \in \text{Contexts. } C \text{ has type } \text{Labels} \rightarrow P(\Sigma)$$
 - For each label i , $C(i)$ = all possible states σ at label i
- This is called the *collecting semantics* of the program
 - Records (super-)set of all possible traces that can reach a program point l
 - This is basically what model checkers approximate!

Back to Abstract Interpretation

- Pick a complete lattice A (abstractions for $\mathcal{P}(\Sigma)$)
 - Along with a monotonic abstraction $\alpha : \mathcal{P}(\Sigma) \rightarrow A$
 - Alternatively, pick $\beta : \Sigma \rightarrow A$
 - This uniquely defines its Galois connection γ
- Take the relations between C_i and move them to the abstract domain:

$$a : \text{Label} \rightarrow A$$

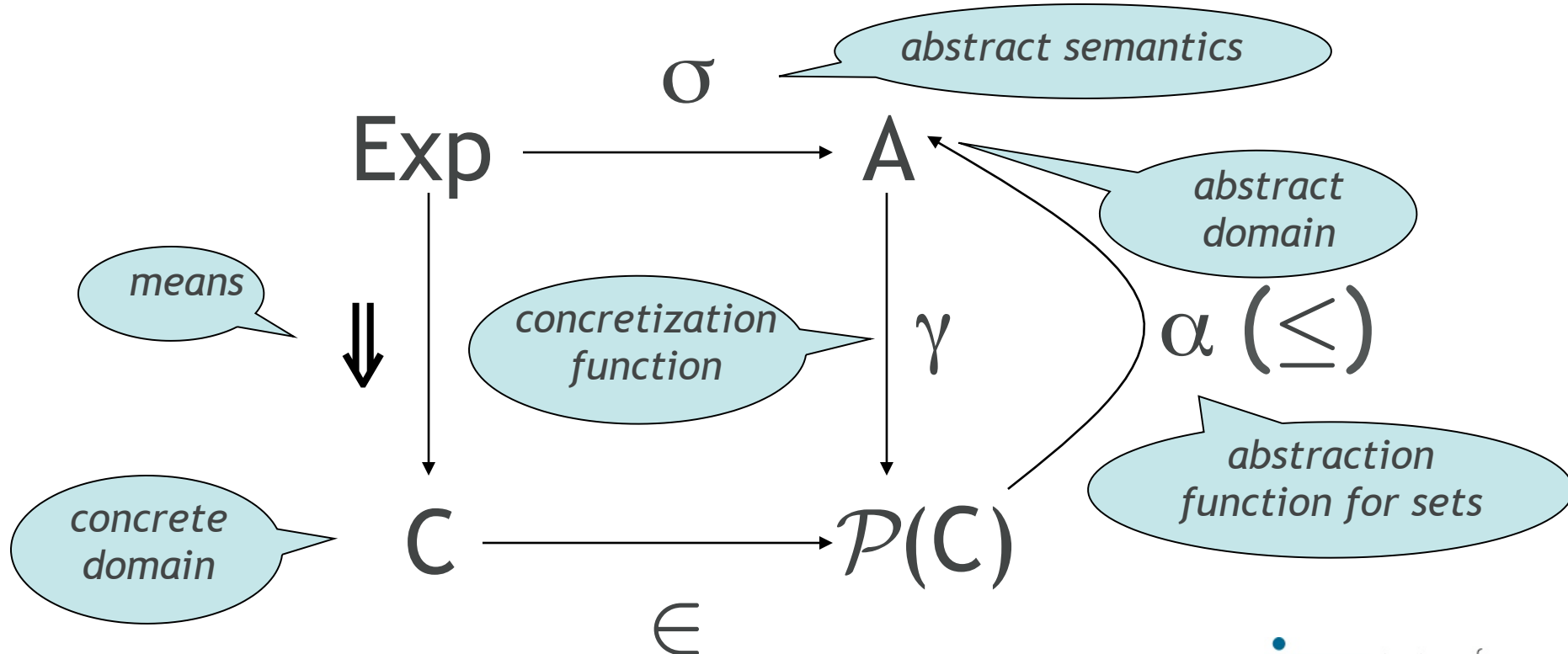
- Assignment

Concrete: $C_j = \{\sigma[x := n] \mid \sigma \in C_i \wedge e \Downarrow \sigma = n\}$

Abstract: $a_j = \alpha \{ \sigma[x := n] \mid \sigma \in \gamma(a_i) \wedge e \Downarrow \sigma = n \}$

Correctness Condition

- In general, abstract interpretation satisfies the following (amazingly common) **diagram**



Other Abstract Domains

- Linear relationships between variables
 - A convex **polyhedron** is a subset of \mathbb{Z}^k whose elements satisfy a number of inequalities:
$$a_1x_1 + a_2x_2 + \dots + a_kx_k \geq c_i$$
 - This is a complete lattice; linear programming methods compute lubs
- Linear relationships with at most two variables
 - Convex polyhedra but with ≤ 2 variables per constraint
 - Octagons ($x + y \geq c$) have efficient algorithms
- Modulus constraints (e.g. even and odd)

Abstract Chatter

- **AI, Dataflow and Software Model Checking**
 - The big three (aside from flow-insensitive type systems) for program analyses
- Are in fact quite related:
 - David Schmidt. *Data flow analysis is model checking of abstract interpretation*. POPL '98.
- AI is usually flow-sensitive (per-label answer)
- AI can be path-sensitive (if your abstract domain includes \vee , for example), which is just where model checking uses BDD's
- Metal, SLAM, ESP, ... can all be viewed as AI

Abstract Interpretation

Conclusions

- AI is a very powerful technique that underlies a large number of program analyses
 - Including Dataflow Analysis and Model Checking
- AI can also be applied to functional and logic programming languages
- There are a few success stories
 - Strictness analysis for lazy functional languages
 - PolySpace for linear constraints
- In most other cases however AI is still slow
- When the lattices have infinite height and widening heuristics are used the result becomes unpredictable

Termination holds when:

- The abstract domain has finite height
 - We've stuck to domains for which this is trivially true so far.
- The flow functions are monotonic
 - We proved this just by looking at the definition of the partial order over the abstract state.

Interval analysis

$$\begin{aligned} L &= \mathbb{N}_\infty \times \mathbb{N}_\infty && \text{where } \mathbb{N}_\infty = \mathbb{N} \cup \{-\infty, \infty\} \\ [l_1, h_1] \sqsubseteq [l_2, h_2] &\text{ iff } l_2 \leq_\infty l_1 \wedge h_1 \leq_\infty h_2 \\ [l_1, h_1] \sqcup [l_2, h_2] &= [\min_\infty(l_1, l_2), \max_\infty(h_1, h_2)] \\ \top &= [-\infty, \infty] \\ \perp &= [\infty, -\infty] \\ \sigma_0 &= \top \\ \alpha(x) &= [x, x] \end{aligned}$$

Flow function

$$f_I \llbracket x := y + z \rrbracket(\sigma) = [x \mapsto [l, h]]\sigma$$

where $l = \sigma(y).low +_{\infty} \sigma(z).low$
and $h = \sigma(y).high +_{\infty} \sigma(z).high$

$$f_I \llbracket x := y + z \rrbracket(\sigma) = \sigma$$

where $\sigma(y) = \perp \vee \sigma(z) = \perp$

No loops.

1. $x := 0$

2. if $x = y$ goto 5

3. $x := x + 1$

4. if $x = y$ goto 5

5. $y := 0$

Loops?

```
1. x := 0
2. if x = y goto 5
3. x := x + 1
4. goto 2
5. y := 0
```

```
1. y := x
2. z := 1
3. while [ y > 1 ] do
4. ([z := z * y] ;
5. [y = y-1])
6. y := 6
```

Example of Non-Termination

- The analysis **never terminates**, or terminates very late if the loop bound is known statically
- It is time to approximate even more: **widening**
- We redefine the join (lub) operator of the lattice to ensure that from $[1..1]$ upon union with $[2..2]$ the result is $[1..+\infty)$ and not $[1..2]$
- Now the sequence of states is
 - $[1..1]$, $[1, +\infty)$, $[1, +\infty)$, Done (no more infinite chains)

Formal Definition of Widening

(Cousot 16.399 “Abstract Interpretation”, 2005)

- A widening $\nabla : (P \times P) \rightarrow P$ on a poset $\langle P, \sqsubseteq \rangle$ satisfies:
 - $\forall x, y \in P. \quad x \sqsubseteq (x \nabla y) \quad \wedge \quad y \sqsubseteq (x \nabla y)$
 - For all **increasing chains** $x^0 \sqsubseteq x^1 \sqsubseteq \dots$ the increasing chain $y^0 =_{\text{def}} x^0, \dots, y^{n+1} =_{\text{def}} y^n \nabla x^{n+1}, \dots$ is **not strictly increasing**.
- Two different main uses:
 - Approximate missing lub. (*Not for us.*)
 - **Convergence acceleration.** (*This is the real use.*)
 - A widening operator can be used to effectively compute an upper approximation of the least fixpoint of $F \in L \nabla L$ starting from below when L is computer-representable but does not satisfy the ascending chain condition.

Formally...

$$W(\perp, l_{\text{current}}) = l_{\text{current}}$$

$$W([l_1, h_1], [l_2, h_2]) = [\min_W(l_1, l_2), \max_W(h_1, h_2)]$$

where $\min_W(l_1, l_2) = l_1$

if $l_1 \leq l_2$

and $\min_W(l_1, l_2) = -\infty$

otherwise

where $\max_W(h_1, h_2) = h_1$

if $h_1 \geq h_2$

and $\max_W(h_1, h_2) = \infty$

otherwise

Properties: 1/2

- Must return an upper bound of operands.
 - Why?

$$\forall I_{\text{previous}}, I_{\text{current}} : I_{\text{previous}} \sqsubseteq W(I_{\text{previous}}, I_{\text{current}}) \wedge \\ I_{\text{current}} \sqsubseteq W(I_{\text{previous}}, I_{\text{current}})$$

Properties: 2/2

- When applied to an ascending chain, the result must be of finite height.
 - Why?

$$I_0^W = I_0 \text{ and } \forall i > 0 : I_i^W = W(I_{i-1}^W, I_i)$$

Loss of precision!

- Nice to apply only when necessary, such as only at loop heads (can be inferred).
- Or: use constants in program. If we have a “nearby” constant, like 10, and we see an ascending chain, we can hold off until the top of the chain reaches the constant.
 - \perp , $[0,0]$, $[0,1]$, $[0,2]$, $[0,3]$, ... becomes \perp , $[0,0]$, $[0,10]$, ...
 - If it keeps ascending, then we widen to infinity.

More formally

$$W(\perp, l_{current}) = l_{current}$$

$$W([l_1, h_1], [l_2, h_2]) = [\min_K(l_1, l_2), \max_K(h_1, h_2)]$$

$$\begin{array}{ll} \text{where } \min_K(l_1, l_2) = l_1 & \text{if } l_1 \leq l_2 \\ \text{and } \min_K(l_1, l_2) = \max(\{k \in K \mid k \leq l_2\}) & \text{otherwise} \\ \text{where } \max_K(h_1, h_2) = h_1 & \text{if } h_1 \geq h_2 \\ \text{and } \max_K(h_1, h_2) = \min(\{k \in K \mid k \geq h_2\}) & \text{otherwise} \end{array}$$

Example

```
1. x := 0
2. y := 1
3. if x=10 goto 7
4. x = x + 1
5. y = y - 1
6. goto 3
7. skip
```

Formal Definition of Widening

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Formal Widening Example

$$[1,1] \nabla [1,2] = [1,+\infty)$$

- Range Analysis on z:

```

L0:  z := 1 ;
L1:  while z < 99 do
L2:    z := z + 1
L3:  done /* z ≥ 99 */
L4:
    
```

$x_{j}^{Li} =_{\text{def}}$ the j th iterative attempt to compute an abstract value for z at label Li

Recall $\text{lub } S = [\min(S)..\max(S)]$
 $\text{lub } \{[2,+\infty), [1,+\infty)\} = \{[1,+\infty)\}$

Original x^i	Widened y^i
$x_{0}^{L0} = \perp$	$y_{0}^{L0} = \perp$
$x_{0}^{L1} = [1,1]$	$y_{0}^{L1} = [1,1]$
$x_{0}^{L2} = [1,1]$	$y_{0}^{L2} = [1,1]$
$x_{0}^{L3} = [2,2]$	$y_{0}^{L3} = [2,2]$
$x_{1}^{L2} = [1,2]$	$y_{1}^{L2} = [1,+\infty)$
$x_{1}^{L3} = [2,+\infty)$	$y_{1}^{L3} = [2,+\infty)$
$x_{0}^{L4} = [99,+\infty)$	$y_{0}^{L4} = [99,+\infty)$
stable (fewer than 99 iterations!)	

One Slide Summary

- In **abstract interpretation**, the **abstraction** function β and **concretization** function γ form a **Galois connection**: they are almost inverses.
- To abstract the **state** σ at each program point we use a **collecting semantics** (the abstract domain holds sets of states). This shows the link between abstract interpretation and **model checking**.
- This will result in recursively-defined equations. We use the **fixed point** theorem to solve them. This shows the link between abstract interpretation and **dataflow analysis**.
- **Widening** operators help accelerate convergence.

Semantics, redux.

- Imagine we want to add a new for loop statement type to While:
- for $(x = e_1, x \text{ op_r } e_2, x := e_3)$ do S done
- Let's specify that, in both big- and small-step semantics.