Static Program Analysis Part 3 – lattices and fixpoints

http://cs.au.dk/~amoeller/spa/

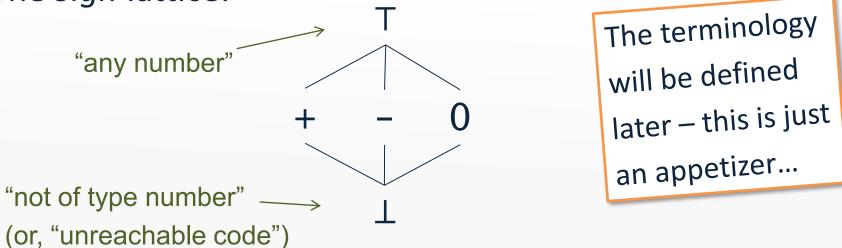
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Flow-sensitivity

- Type checking is (usually) flow-*insensitive*:
 - statements may be permuted without affecting typability
 - constraints are naturally generated from AST nodes
- Other analyses must be flow-*sensitive*:
 - the order of statements affects the results
 - constraints are naturally generated from control flow graph nodes

Sign analysis

- Determine the sign (+,−,0) of all expressions
- The *Sign* lattice:



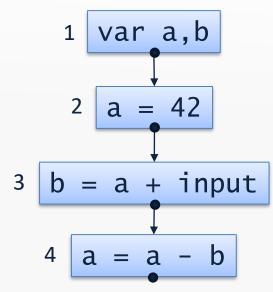
 States are modeled by the map lattice Vars → Sign where Vars is the set of variables in the program

Implementation: TIP/src/tip/analysis/SignAnalysis.scala

Generating constraints

1 var a,b; 2 a = 42; 3 b = a + input; 4 a = a - b;





 $x_1 = [a \mapsto T, b \mapsto T]$ $x_2 = x_1[a \mapsto +]$ $x_3 = x_2[b \mapsto x_2(a) + T]$ $x_4 = x_3[a \mapsto x_3(a) - x_3(b)]$

Sign analysis constraints

- The variable [[v]] denotes a map that gives the sign value for all variables at the program point *after* node v
- For variable declarations:

 $\llbracket \operatorname{var} x_1, \dots, x_n \rrbracket = JOIN(v)[x_1 \mapsto \top, \dots, x_n \mapsto \top]$

• For assignments:

 $[[x = E]] = JOIN(v)[x \mapsto eval(JOIN(v), E)]$

• For all other nodes:

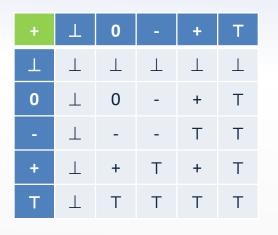
[[v]] = *JOIN*(v)

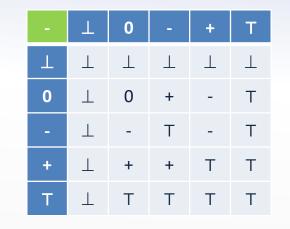
where $JOIN(v) = \bigsqcup [w]$ $w \in pred(v)$ combines information from predecessors (explained later...)

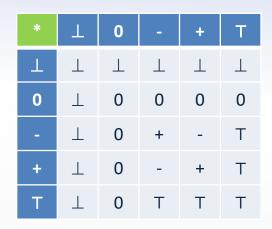
Evaluating signs

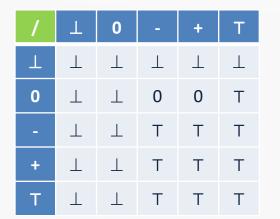
- The *eval* function is an *abstract evaluation*:
 - $eval(\sigma, x) = \sigma(x)$
 - $eval(\sigma, intconst) = sign(intconst)$
 - $eval(\sigma, E_1 \text{ op } E_2) = \overline{\text{op}}(eval(\sigma, E_1), eval(\sigma, E_2))$
- $\sigma: Vars \rightarrow Sign$ is an abstract state
- The *sign* function gives the sign of an integer
- The op function is an abstract evaluation of the given operator

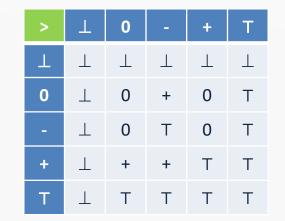
Abstract operators

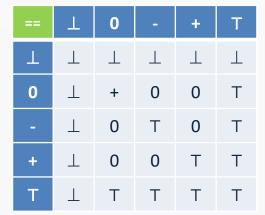








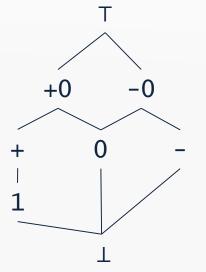




(assuming the subset of TIP with only integer values)

Increasing precision

- Some loss of information:
 - (2>0)==1 is analyzed as T
 - +/+ is analyzed as T, since e.g. $\frac{1}{2}$ is rounded down
- Use a richer lattice for better precision:



Abstract operators are now 8×8 tables

Partial orders

 Given a set S, a partial order ⊑ is a binary relation on S that satisfies:

 $\forall x, y, z \in S: x \sqsubseteq y \land y \sqsubseteq z \Longrightarrow x \sqsubseteq z$

- reflexivity: $\forall x \in S: x \sqsubseteq x$
- transitivity:
- anti-symmetry: $\forall x, y \in S: x \sqsubseteq y \land y \sqsubseteq x \Longrightarrow x = y$
- Can be illustrated by a Hasse diagram (if finite)

Upper and lower bounds

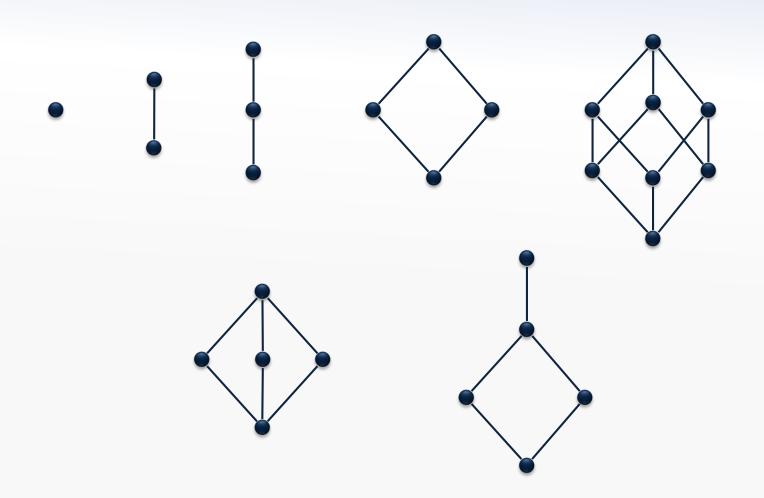
- Let $X \subseteq S$ be a subset
- We say that $y \in S$ is an *upper* bound (X \sqsubseteq y) when $\forall x \in X: x \sqsubseteq y$
- We say that $y \in S$ is a *lower* bound ($y \sqsubseteq X$) when $\forall x \in X: y \sqsubseteq x$
- A *least* upper bound $\sqcup X$ is defined by $X \sqsubseteq \sqcup X \land \forall y \in S: X \sqsubseteq y \Rightarrow \sqcup X \sqsubseteq y$
- A greatest lower bound $\prod X$ is defined by $\prod X \sqsubseteq X \land \forall y \in S: y \sqsubseteq X \Rightarrow y \sqsubseteq \prod X$

Lattices

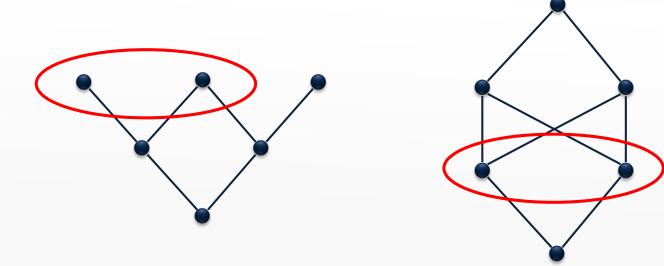
- A (complete) *lattice* is a partial order where $\sqcup X$ and $\sqcap X$ exist for all $X \subseteq S$
- A lattice must have
 - a unique largest element, $T = \bigsqcup S$ (exercise)
 - a unique smallest element, $\perp = \prod S$
- If S is a finite set, then it defines a lattice iff
 - \top and \perp exist in S
 - x⊔y and x⊓y exist for all x,y ∈ S (x⊔y is notation for $\bigsqcup{x,y}$)

Implementation: TIP/src/tip/lattices/

These partial orders are lattices

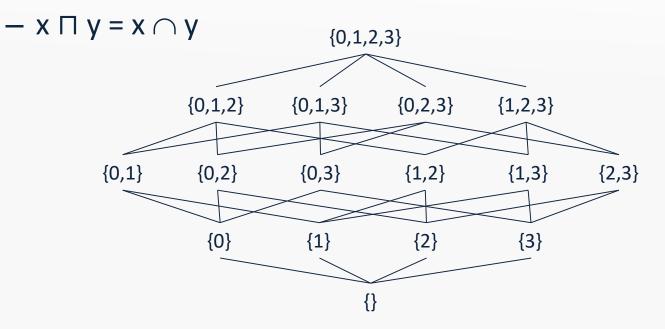


These partial orders are not lattices



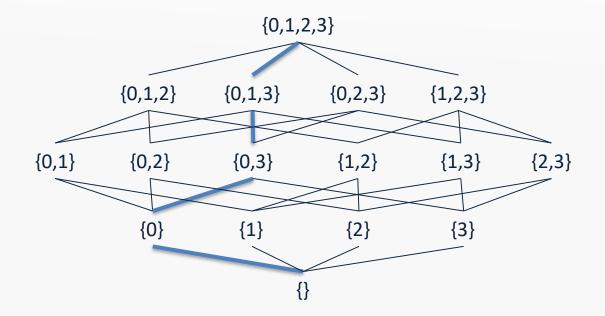
The powerset lattice

- Every finite set A defines a lattice (2^A,⊆) where
 - $\perp = \emptyset$
 - T = A
 - $x \sqcup y = x \cup y$



Lattice height

- The *height* of a lattice is the length of the longest path from \bot to \top
- The lattice (2^A,⊆) has height |A|



Map lattice

• If A is a set and L is a lattice, then we obtain the map lattice:

 $A \to L = \{ [a_1 \mapsto x_1, a_2 \mapsto x_2, ...] \mid A = \{a_1, a_2, ...\} \land x_1, x_2, ... \in L \}$

ordered pointwise

Example: $A \rightarrow L$ where

- A is the set of program variables
- L is the Sign lattice
- ⊔ and ⊓ can be computed pointwise
- $height(A \rightarrow L) = |A| \cdot height(L)$

Product lattice

• If L₁, L₂, ..., L_n are lattices, then so is the *product*:

$$L_1 \times L_2 \times ... \times L_n = \{ (x_1, x_2, ..., x_n) | x_i \in L_i \}$$

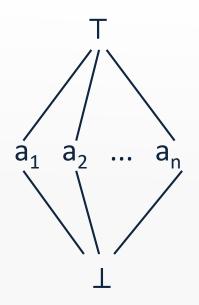
where \sqsubseteq is defined pointwise

- Note that ⊔ and ⊓ can be computed pointwise
- $height(L_1 \times L_2 \times ... \times L_n) = height(L_1) + ... + height(L_n)$

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Example: each L_i is the map lattice A \rightarrow L from the previous slide, and n is the number of CFG nodes
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Flat lattice

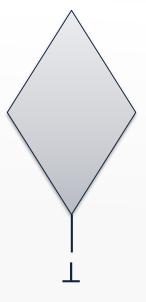
• If A is a set, then *flat*(A) is a lattice:



height(flat(A)) = 2

Lift lattice

• If L is a lattice, then so is *lift*(L), which is:



height(lift(L)) = height(L)+1

Sign analysis constraints, revisited

- The variable [[v]] denotes a map that gives the sign value for all variables at the program point *after* node v
- $\llbracket v \rrbracket \in States$ where $States = Vars \rightarrow Sign$
- For variable declarations:

 $\llbracket \operatorname{var} x_1, \dots, x_n \rrbracket = JOIN(v)[x_1 \mapsto \top, \dots, x_n \mapsto \top]$

• For assignments:

 $[[x = E]] = JOIN(v)[x \mapsto eval(JOIN(v), E)]$

• For all other nodes:

[[v]] = *JOIN*(v)

```
where JOIN(v) = \bigsqcup_{w \in pred(v)} \llbracket w \rrbracket
```

combines information from predecessors

```
var a,b,c;
a = 42;
b = 87;
if (input) {
    c = a + b;
} else {
    c = a - b;
}
```

Generating constraints



 $\llbracket entry \rrbracket = \bot$ $\llbracket var a, b, c \rrbracket = \llbracket entry \rrbracket [a \mapsto T, b \mapsto T, c \mapsto T]$ $[a = 42] = [var a, b, c] [a \mapsto +]$ $[b = 87] = [a = 42][b \mapsto +]$ [[input]] = [[b = 87]] $[[c = a + b]] = [[input]][c \mapsto [[input]](a) + [[input]](b)]$ $[[c = a - b]] = [[input]][c \mapsto [[input]](a) - [[input]](b)]$ using $[.u.b. \rightarrow [[exit]] = [[c = a + b]] \sqcup [[c = a - b]]$

Constraints

• From the program being analyzed, we have constraint variables x₁, ..., x_n∈L and a collection of constraints:

- These can be collected into a single function f: $L^n \rightarrow L^n$: $f(x_1,...,x_n) = (f_1(x_1,...,x_n), ..., f_n(x_1,...,x_n))$
- How do we find the least (i.e. most precise) value of
 x₁,...,x_n such that x₁,...,x_n = f(x₁,...,x_n) (if that exists)???

Monotone functions

• A function f: $L \rightarrow L$ is *monotone* when

 $\forall x,y \in L: x \sqsubseteq y \Longrightarrow f(x) \sqsubseteq f(y)$

- A function with several arguments is monotone if it is monotone in each argument
- Monotone functions are closed under composition
- As functions, ⊔ and ⊓ are both monotone (exercises)
- $x \sqsubseteq y$ can be interpreted as "x is at least as precise as y"
- When f is monotone:

"more precise input cannot lead to less precise output"

A *least* upper bound $\bigsqcup X$ is defined by $X \sqsubseteq \bigsqcup X \land \forall y \in S: X \sqsubseteq y \Rightarrow \bigsqcup X \sqsubseteq y$ A *greatest* lower bound $\bigsqcup X$ is defined by $\bigsqcup X \sqsubseteq X \land \forall y \in S: y \sqsubseteq X \Rightarrow y \sqsubseteq \bigsqcup X$

x \sqcup y and x \sqcap y exist for all x,y \in S (x \sqcup y is notation for \sqcup {x,y})

Monotonicity for the sign analysis

Example, constraints for assignments: $[[x = E]] = JOIN(v)[x \mapsto eval(JOIN(v), E)]$

- The ⊔ operator and map updates are monotone
- Compositions preserve
 monotonicity
- Are the abstract operators monotone?
- Can be verified by a tedious inspection:

 $- \forall x, y, x' \in L: x \sqsubseteq x' \Longrightarrow x \ \overline{\text{op}} \ y \sqsubseteq x' \ \overline{\text{op}} \ y$

 $- \forall x, y, y' \in \mathsf{L}: y \sqsubseteq y' \Longrightarrow x \ \overline{\mathsf{op}} \ y \sqsubseteq x \ \overline{\mathsf{op}} \ y'$

(exercises)

Kleene's fixed-point theorem

 $x \in L$ is a *fixed-point* of f: L \rightarrow L iff f(x)=x

In a lattice with finite height, every monotone function f has a *unique least fixed-point*:

 $fix(f) = \bigsqcup_{i \ge 0} f^i(\bot)$

克莱尼不动点定理:序理论的不动点定理 L:完全格 f是单调函数 f的最小不动点是f的升 Kleene链的最小上界,这个链是在L的底元素上迭代f而获得

Proof of existence

- Clearly, $\bot \sqsubseteq f(\bot)$
- Since f is monotone, we also have $f(\bot) \sqsubseteq f^2(\bot)$
- By induction, $f^{i}(\bot) \sqsubseteq f^{i+1}(\bot)$
- This means that

 $\bot \sqsubseteq f(\bot) \sqsubseteq f^2(\bot) \sqsubseteq \dots f^i(\bot) \dots$

is an increasing chain

- L has finite height, so for some k: $f^{k}(\bot) = f^{k+1}(\bot)$
- If $x \sqsubseteq y$ then $x \sqcup y = y$ (exercise)
- So fix(f) = $f^k(\bot)$

Proof of unique least

- Assume that x is another fixed-point: x = f(x)
- Clearly, $\bot \sqsubseteq x$
- By induction, $f^i(\bot) \sqsubseteq f^i(x) = x$
- In particular, $fix(f) = f^k(\bot) \sqsubseteq x$, i.e. fix(f) is least
- Uniqueness then follows from anti-symmetry

Computing fixed-points

The time complexity of *fix*(f) depends on:

- the height of the lattice
- the cost of computing f
- the cost of testing equality

Implementation: TIP/src/tip/solvers/FixpointSolvers.scala

Summary: lattice equations

- Let L be a lattice with finite height
- A *equation system* is of the form:

$$x_1 = f_1(x_1, ..., x_n)$$

 $x_2 = f_2(x_1, ..., x_n)$

$$x_n = f_n(x_1, ..., x_n)$$

where x_i are variables and each $f_i: L^n \rightarrow L$ is monotone

• Note that Lⁿ is a product lattice

Solving equations

 Every equation system has a unique least solution, which is the least fixed-point of the function f: Lⁿ→Lⁿ defined by

 $f(x_1,...,x_n) = (f_1(x_1,...,x_n), ..., f_n(x_1,...,x_n))$

- A solution is always a fixed-point (for any kind of equation)
- The least one is the most precise

Solving inequations

- A *inequation system* is of the form
 - $x_1 \sqsubseteq f_1(x_1, ..., x_n)$ $x_1 \sqsupseteq f_1(x_1, ..., x_n)$ $x_2 \sqsubseteq f_2(x_1, ..., x_n)$ or $x_2 \sqsupseteq f_2(x_1, ..., x_n)$ $x_n \sqsubseteq f_n(x_1, ..., x_n)$ $x_n \sqsupseteq f_n(x_1, ..., x_n)$
- Can be solved by exploiting the facts that

 $x \sqsubseteq y \iff x = x \sqcap y$

and

 $x \supseteq y \Leftrightarrow x = x \sqcup y$

Monotone frameworks

John B. Kam, Jeffrey D. Ullman: Monotone Data Flow Analysis Frameworks. Acta Inf. 7: 305-317 (1977)

- A CFG to be analyzed, nodes Nodes = {v₁, v₂, ..., v_n}
- A finite-height lattice L of possible answers
 fixed or parametrized by the given program
 - A constraint variable $[v_i]$ at far every CEC near
- A constraint variable [[v]] ∈ L for every CFG node v
- A dataflow constraint for each syntactic construct
 - relates the value of $[\![v]\!]$ to the variables for other nodes
 - typically a node is related to its neighbors
 - the constraints must be monotone functions:

 $\llbracket \mathbf{v}_i \rrbracket = \mathbf{f}_i(\llbracket \mathbf{v}_1 \rrbracket, \llbracket \mathbf{v}_2 \rrbracket, ..., \llbracket \mathbf{v}_n \rrbracket)$

Monotone frameworks

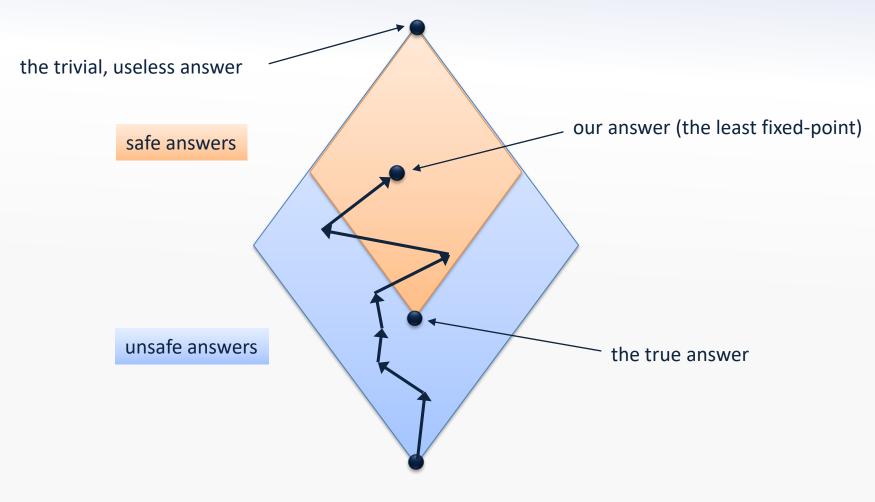
- Extract all constraints for the CFG
- Solve constraints using the fixed-point algorithm:
 - we work in the lattice Lⁿ where L is a lattice describing abstract states
 - computing the least fixed-point of the combined function: $f(x_1,...,x_n) = (f_1(x_1,...,x_n), ..., f_n(x_1,...,x_n))$
- This solution gives an answer from L for each CFG node

Generating and solving constraints



Conceptually, we separate constraint generation from constraint solving, but in implementations, the two stages are typically interleaved

Lattice points as answers



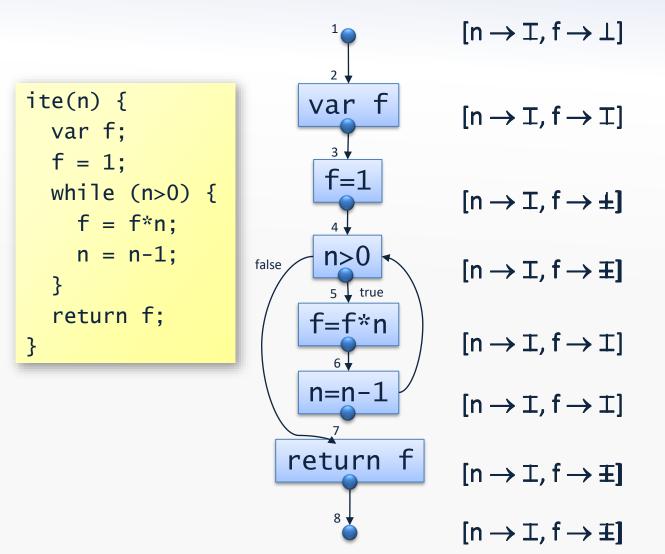
Conservative approximation...

The naive algorithm

- Correctness ensured by the fixed point theorem
- Does not exploit any special structure of Lⁿ or f
 (i.e. x∈Lⁿ and f(x₁,...,x_n) = (f₁(x₁,...,x_n), ..., f_n(x₁,...,x_n)))

Implementation: SimpleFixpointSolver

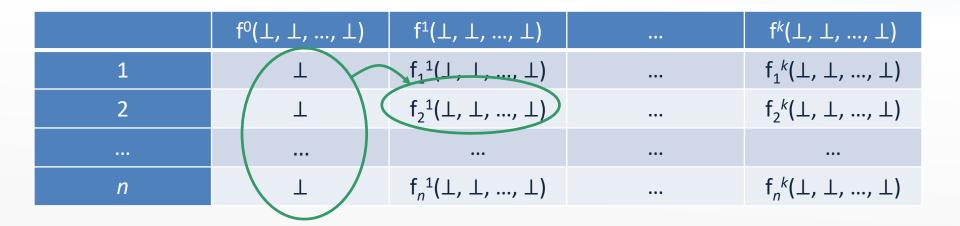
Example: sign analysis



Note: some of the constraints are mutually recursive in this example

(We shall later see how to improve precision for the loop condition)

The naive algorithm



Computing each new entry is done using the previous column

- Without using the entries in the current column that have already been computed!
- And many entries are likely unchanged from one column to the next!

Chaotic iteration

Recall that $f(x_1,...,x_n) = (f_1(x_1,...,x_n), ..., f_n(x_1,...,x_n))$

We now exploit the special structure of Lⁿ

 may require a higher number of iterations, but less work in each iteration

Correctness of chaotic iteration

- Let x^j be the value of x=(x₁, ..., x_n) in the j'th iteration of the naive algorithm
- Let <u>x^j</u> be the value of x=(x₁, ..., x_n) in the j'th iteration of the chaotic iteration algorithm
- By induction in j, show $\forall j: \underline{x^j} \sqsubseteq x^j$
- Chaotic iteration eventually terminates at a fixed point
- It must be identical to the result of the naive algorithm since that is the least fixed point

Towards a practical algorithm

- Computing ∃i:... in chaotic iteration is not practical
- Idea: predict i from the analysis and the structure of the program!
- Example: In sign analysis, when we have processed a CFG node v, process succ(v) next

The worklist algorithm (1/2)

- Essentially a specialization of chaotic iteration that exploits the special structure of f
- Most right-hand sides of f_i are quite sparse:
 constraints on CFG nodes do not involve all others
- Use a map:

dep: Nodes $\rightarrow 2^{Nodes}$

that for $v \in Nodes$ gives the variables w where v occurs on the right-hand side of the constraint for w

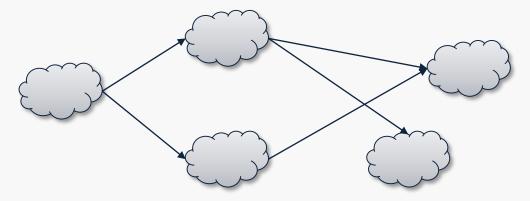
The worklist algorithm (2/2)

$$\begin{array}{l} x_{1} = \bot; \hdots x_{n} = \bot; \\ W = \{v_{1}, \hdots, v_{n}\}; \\ \mbox{while } (W \neq \varnothing) \{ \\ v_{i} = W. removeNext(); \\ y = f_{i}(x_{1}, \hdots, x_{n}); \\ \mbox{if } (y \neq x_{i}) \{ \\ for (v_{j} \in dep(v_{i})) \ W. add(v_{j}); \\ x_{i} = y; \\ \} \\ \end{array}$$

Implementation: SimpleWorklistFixpointSolver

Further improvements

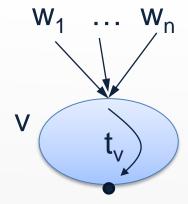
- Represent the worklist as a priority queue
 - find clever heuristics for priorities
- Look at the graph of dependency edges:
 - build strongly-connected components
 - solve constraints bottom-up in the resulting DAG



Transfer functions

• The constraint functions in dataflow analysis usually have this structure:

 $\llbracket v \rrbracket = t_v(JOIN(v))$ where t_v: *States* \rightarrow *States* is called the *transfer function* for v



• Example:

 $\begin{bmatrix} x = E \end{bmatrix} = JOIN(v)[x \mapsto eval(JOIN(v), E)]$ $= t_v(JOIN(v))$

where

 $t_v(s) = s[x \mapsto eval(s,E)]$

Sign Analysis, continued...

- Another improvement of the worklist algorithm:
 - only add the entry node to the worklist initially
 - then let dataflow propagate through the program according to the constraints...
- Now, what if the constraint rule for variable declarations was:
 [var x₁, ..., x_n]] = JOIN(v)[x₁ ↦ ⊥, ..., x_n ↦ ⊥]

(would make sense if we treat "uninitialized" as "no value" instead of "any value")

- Problem: iteration would stop before the fixpoint!
- Solution: replace Vars → Sign by lift(Vars → Sign)
 (allows us to distinguish between "unreachable" and "all variables are non-integers")
- This trick is also useful for context-sensitive analysis! (later...)

Inheritance and Software Reuse

- Virtual Inheritance
 - C++ 为解决Diamond 继承问题而提出的解决方案
 - Bjarne Stroustrup 的*Multiple Inheritance for C++*
- <u>Mixin</u>
 - 类中的方法可以被其他类使用而不必是其他类的父类
 - Gilad Bracha 等 Mixin-based Inheritance [OOPSLA1990]
- Traits
 - 一组方法可以用于扩展一个类的功能
 - 源于Self 语言, Traits: An approach to multiple-inheritance subclassing [SIGOA 1982]
 - Oscar Nierstrasz 等的 Traits: Composable Units of Behaviour[ECOOP 2003]
- Prototypal Inheritance
 - 通过原型来对现有的对象进行复用
 - 源于Self 语言
 - <u>Classifying Prototype-based Programming Languages</u>和 <u>Prototypal</u> <u>Inheritance in JavaScript</u>

Generic Programming

- STL(Standard Template Library)
 - <u>Alexander Stepanov</u> 是 C++ STL的主要设计和实现者
 - C++ STL于1994年向 ANSI/ISO C++ 标准委员会建议,后 经少量修改和扩展于1997年成为官方的 C++ 标准的一部分
- Concepts
 - 是对一个类型中所支持的操作的描述,包括语法和语义
 - 最早于1998年在 STL 中使用 <u>Concepts: The Future of</u> <u>Generic Programming</u>,该术语出自 <u>Alexander Stepanov</u>
 - <u>a bit of background for concepts and C++17—Bjarne</u> <u>Stroustrup</u>

FixpointSolvers

- LatticeSolver
 - [lattice | <u>analyze()</u>]
- A <u>SimpleFixpointSolver</u> : LatticeSolver
 - [|<u>analyze()</u>, <u>fun()</u>]
- MapLatticeSolver[N] :LatticeSolver with Dependencies[N]
 - [|<u>transfer()</u>, <u>funsub()</u>, <u>join()</u>]
- <u>SimpleMapLatticeFixpointSolver[N]</u>: SimpleFixpointSolver with MapLatticeSolver[N]
 - [domain | <u>fun(</u>)]
- <u>MapLiftLatticeSolver[N]</u>: MapLatticeSolver[N] with Dependencies[N]
- <u>Worklist[N]</u> N: type of the elements in the worklist
 - [|process(), add(), run()]
- <u>ListSetWorklist[N]</u> : Worklist[N]
 - [worklist | add(), run()]
- <u>WorklistFixpointSolver[N]</u>: MapLatticeSolver[N] with ListSetWorklist[N] with Dependencies[N]
 - [x | process()]
- <u>SimpleWorklistFixpointSolver[N]</u>: WorklistFixpointSolver[N]
- <u>WorklistFixpointSolverWithReachability</u>[N] extends WorklistFixpointSolver[N] with MapLiftLatticeSolver[N]

Exercise 4.2: Prove that if $x \sqcup y$ exists then $x \sqsubseteq y \Leftrightarrow x \sqcup y = y$, and conversely, if $x \sqcap y$ exists then $x \sqsubseteq y \Leftrightarrow x \sqcap y = x$.

Exercise 4.6: Prove that [] S and [] S are the unique largest element and the unique smallest element, respectively, in S. In other words, we have $\top = [] S$ and $\bot = [] S$.

Exercise 4.16: A function $f: L \to L$ where L is a lattice is *extensive* when $\forall x \in L: x \sqsubseteq f(x)$. Assume L is the powerset lattice $2^{\{0,1,2,3,4\}}$ Give examples of different functions $L \to L$ that are, respectively,

- (a) extensive and monotone,
- (b) extensive but not monotone,
- (c) not extensive but monotone, and
- (d) not extensive and not monotone.

Exercise 4.18: A function $f: L_1 \to L_2$ where L_1 and L_2 are lattices is *distributive* when $\forall x, y \in L_1: f(x) \sqcup f(y) = f(x \sqcup y)$.

(a) Show that every distributive function is also monotone.

(b) Show that not every monotone function is also distributive.

Exercise 4.29: Does the fixed-point theorem also hold without the assumption that *f* is monotone? If yes, give a proof; if no, give a counterexample.

Exercise 4.30: Does the fixed-point theorem also hold without the assumption that the lattice has finite height? If yes, give a proof; if no, give a counterexample.