Abstract Interpretation Non-Standard Semantics

Lecture 8-9 ECS 240

The Problem

- It is useful to predict program behavior statically (without running the program)
 - For optimizing compilers
 - For software engineering tools
- The semantics we studied so far give us the precise semantics
- However, precise static predictions are impossible
 - The exact semantics is not computable
- We must settle for approximate, but correct static analysis (e.g. VC vs. WP)

- We will introduce abstract interpretation by example
- Starting with a miniscule language we will build up to a fairly realistic application
- Along the way we will see most of the ideas and difficulties that arise in a big class of applications

A Tiny Language

- Consider the following language of arithmetic $e ::= n | e_1 * e_2$
- The denotational semantics of this language

$$[n] = n$$

 $[e_1 * e_2] = [e_1] \times [e_2]$

• For this language the precise semantics is computable

An Abstraction

- Assume that we are interested not in the value of the expression, but only in its sign:
 - positive (+), negative (-), or zero (0)
- We can define an <u>abstract semantics</u> that computes only the sign of the result

 $\sigma \mbox{:} \mbox{Exp} \rightarrow \mbox{-, 0, +}$

$$\sigma(n) = sign(n)$$

 $\sigma(e_1 * e_2) = \sigma(e_1) \otimes \sigma(e_2)$

\otimes	-	0	+
-	+	0	-
0	0	0	0
+	-	0	+

Correctness of Sign Abstraction

 We can show that the abstraction is correct in the sense that it correctly predicts the sign

 $\llbracket e \rrbracket > 0 \Leftrightarrow \sigma(e) = +$ $\llbracket e \rrbracket = 0 \Leftrightarrow \sigma(e) = 0$ $\llbracket e \rrbracket < 0 \Leftrightarrow \sigma(e) = -$

- Our semantics is abstract but precise
- Proof is by structural induction on expression e
 - Each case repeats similar reasoning

Another View of Soundness

• We associate with each concrete value an abstract value:

$$eta:\mathbb{Z} o$$
 { -, 0, + }

- This is called the <u>abstraction function</u>
- Conversely we can also define the <u>concretization</u> <u>function</u>:

$$\gamma: \{\text{-}, \text{0}, \text{+}\} \rightarrow \mathcal{P}(\mathbb{Z})$$

$$γ(+) = { n ∈ ℤ | n > 0 }$$

 $γ(0) = { 0 }$
 $γ(-) = { n ∈ ℤ | n < 0 }$

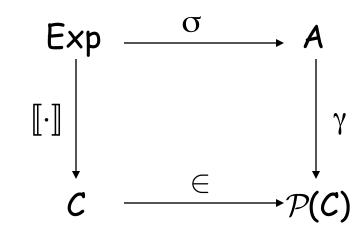
Another View of Soundness (Cont.)

Soundness can be stated succinctly

$$\forall e \in \mathsf{Exp.} \llbracket e \rrbracket \in \gamma(\sigma(e))$$

(the true value of the expression is among the concrete values represented by the abstract value of the expression)

• Let C be the concrete domain (e.g. \mathbb{Z}) and A be the abstract domain (e.g. {-, 0, +})



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Another View of Soundness (Cont.)

- Consider the generic abstraction of an operator $\sigma(e_1 \text{ op } e_2) = \sigma(e_1) \underline{op} \sigma(e_2)$
- This is sound iff $\forall a_1 \forall a_2. \gamma(a_1 \text{ op } a_2) \supseteq \{n_1 \text{ op } n_2 \mid n_1 \in \gamma(a_1), n_2 \in \gamma(a_2)\}$
- E.g. $\gamma(a_1 \otimes a_2) \supseteq \{ n_1 * n_2 \mid n_1 \in \gamma(a_1), n_2 \in \gamma(a_2) \}$
- This reduces the proof of correctness to one proof for each operator

- This is our first example of an <u>abstract</u> <u>interpretation</u>.
- We carry out computation in an abstract domain
- The abstract semantics is a sound approximation of the standard semantics
- The concretization and abstraction functions establish the connection between the two domains

Adding Unary Minus and Addition

- We extend the language to $e ::= n | e_1 * e_2 | e$
- We define $\sigma(-e) = \ominus \sigma(e)$

	-	0	+
\bigcirc	+	0	-

- Now we add addition: $e ::= n | e_1 * e_2 | e | e_1 + e_2$
- We define $\sigma(e_1 + e_2) = \sigma(e_1) \oplus \sigma(e_2)$

\oplus	-	0	+
1	-	-	?
0	-	0	+
+	?	+	+

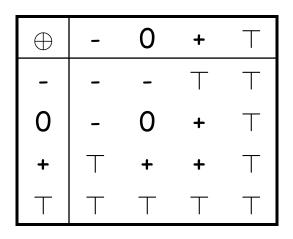
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Adding Addition

- The sign values are not closed under addition
- What should be the value of "+ \oplus -"?
- Start from the soundness condition:

 $\gamma(+ \oplus -) \supseteq \{ \mathsf{n}_1 + \mathsf{n}_2 \mid \mathsf{n}_1 > \mathsf{0}, \mathsf{n}_2 < \mathsf{0} \} = \mathbb{Z}$

- We don't have an abstract value whose concretization includes $\mathbb Z$, so we add one: \top



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Examples

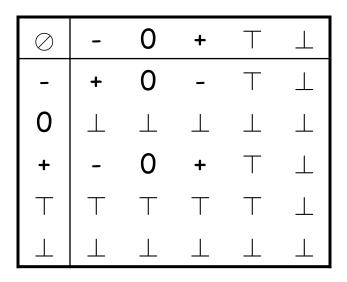
Abstract computation might loose information

[[(1+2)+-3]] = 0 $\sigma((1+2)+-3) = (\sigma(1) \oplus \sigma(2)) \oplus \sigma(-3) = (+ \oplus +) \oplus - = \top$

- We loose some precision
- But this will simplify the computation of the abstract answer in cases when the precise answer is not computable

Adding Division

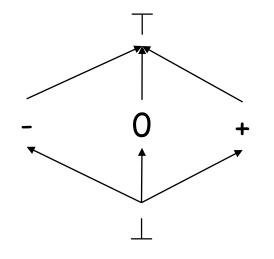
- Fairly straightforward except for division by 0
 - We say that there is no answer in that case
 - γ (+ \oslash 0) = { n | n = n₁ / 0 , n₁ > 0 } = Ø
- We introduce \perp to be the abstraction of the \emptyset
 - We also use the same abstraction for non-termination !



- Our abstract domain forms a lattice
 - A partial order is induced by $\boldsymbol{\gamma}$

 $a_1 \leq a_2$ iff $\gamma(a_1) \subseteq \gamma(a_2)$

- We say that a_1 is more precise that a_2 !
- Every <u>finite subset</u> has a least-upper bound (lub) and a greatest-lower bound (glb)



Lattice Facts

- A lattice is <u>complete</u> when all subsets have lub and glb
 - Even infinite ones
- Every finite lattice is complete
- Every complete lattice is a CPO
 - Since a chain is a subset
- Not every CPO is a complete lattice
 - Might not even be a lattice

- Early work in denotational semantics used lattices
 - But it was latter seen that only chains need to have lub
 - And there was no need for \top and glb

- In abstract interpretation we'll use \top to denote "I don't know"
 - Corresponds to all values in the concrete domain

More Definitions

- We can start with the <u>abstraction function</u>
 - $\beta: \mathcal{C} \rightarrow \mathcal{A}$ (maps a concrete value to the best abstract value)
 - A must be a lattice
- From here we can derive the concretization function

 $egin{array}{ll} \gamma: {old A} o {\mathcal P}({old C}) \ \gamma({old a}) = \{ \ {old X} \in {old C} \ | \ eta({old X}) \leq {old a} \ \} \end{array}$

And the abstraction for sets

 $lpha : \mathcal{P}(\mathcal{C}) \rightarrow \mathcal{A}$ $lpha(S) = \mathsf{lub} \{ \beta(x) \mid x \in S \}$

Example

• Consider our sign lattice

$$\beta(n) = \begin{cases} + & \text{if } n > 0 \\ 0 & \text{if } n = 0 \\ - & \text{if } n < 0 \end{cases}$$

•
$$\alpha(S) = \mathsf{lub} \{ \beta(x) \mid x \in S \}$$

- Example:
$$\alpha$$
 ({1, 2}) = lub { + } = +
 α ({1, 0}) = lub { +, 0} = \top
 α ({}) = lub {} = \bot

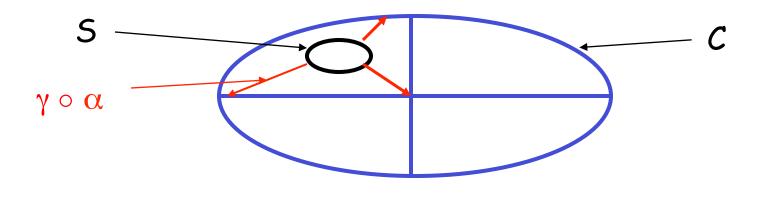
•
$$\gamma(a) = \{ n \mid \beta(n) \le a \}$$

- Example: $\gamma(+) = \{ n \mid \beta(n) \le + \} = \{ n \mid \beta(n) = +\} = \{ n \mid n > 0 \}$
 $\gamma(\top) = \{ n \mid \beta(n) \le \top \} = \mathbb{Z}$
 $\gamma(\bot) = \{ n \mid \beta(n) \le \bot \} = \emptyset$

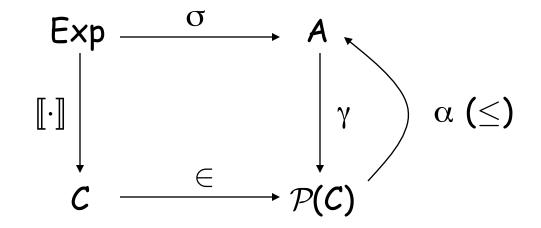
Galois Connections

- We can show that
 - γ and α are monotonic (with the \subseteq ordering on $\mathcal{P}(\mathcal{C})$)
 - α (γ (α)) = a for all $a \in A$
 - γ (α (S)) \supseteq S for all S $\in \mathcal{P}(C)$
- Such a pair of functions is called a Galois connection

- Between lattices A and $\mathcal{P}(C)$



 In general, abstract interpretation satisfies the following diagram



Conditions for correct abstract interpretations

- 1. α and γ are monotonic
- 2. α and γ form a Galois connection
- 3. Abstraction of operations is correct $a_1 \text{ op } a_2 = \alpha(\gamma(a_1) \text{ op } \gamma(a_2))$

- Introduced abstract interpretation
- Two mappings form a Galois connection
 - An abstraction mapping from concrete to abstract values
 - A concretization mapping from abstract to concrete values
- Next look a bit more at Galois connections
- Then extend these ideas from expressions to programs

Why Galois Connections ?

- We have an abstract domain A
 - An abstraction function $\beta:\mathbb{Z}\to \textbf{A}$
 - Induces $\alpha : \mathcal{P}(\mathbb{Z}) \to A \text{ and } \gamma : A \to \mathcal{P}(\mathbb{Z})$
- We argued that for correctness

 $\gamma(a_1 \text{ op } a_2) \supseteq \gamma(a_1) \text{ op } \gamma(a_2)$

- We wish for the set on the left to be as small as possible
- To reduce the loss of information through abstraction
- For each set $S \subseteq C$, define $\alpha(S)$ as follows:
 - Pick S' the smallest that includes S and is in the image of γ
 - Define $\alpha(S) = \gamma^{-1}(S')$
 - Then we define: $a_1 \underline{op} a_2 = \alpha(\gamma(a_1) op \gamma(a_2))$
- Then α and γ form a Galois connection

Abstract Interpretation for Imperative Programs

- So far we abstracted the value of expressions
- We want now to abstract the state at each point in the program
- First we define the concrete semantics that we are abstracting
 - We use a <u>collecting semantics</u>

The Collecting Semantics

- Recall
 - A state $\sigma \in \Sigma$ = Var $\rightarrow \mathbb{Z}$
 - States vary from program point to program point
- We introduce a set of program points: Labels
- We want to answer questions like:
 - Is x always positive at label i?
 - Is x always greater or equal to y at label j?
- To answer these questions it helps to construct

 $\mathcal{C} \in \mathcal{C}$ ontexts = Labels $ightarrow \mathcal{P}(\Sigma)$

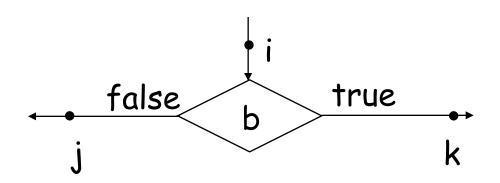
- For each label, all the states at that label
- This is called the <u>collecting semantics</u> of the program
- How can we define the collecting semantics ?

Defining the Collecting Semantics

- We first define relations between the collecting semantics at different labels
 - We do it for a flowchart program
 - It can be done for IMP with careful definition of program points
- Define a label on each edge in the flowchart
- For assignment

Defining the Collecting Semantics

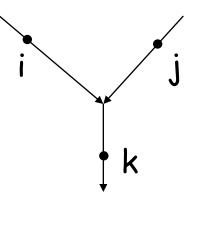
For conditionals



$$\begin{array}{l} \textbf{C}_{j} \texttt{=} \{ \ \sigma \ | \ \sigma \in \textbf{C}_{i} \land \llbracket \texttt{b} \rrbracket \sigma \texttt{=} \texttt{false} \} \\ \textbf{C}_{k} \texttt{=} \{ \ \sigma \ | \ \sigma \in \textbf{C}_{i} \land \llbracket \texttt{b} \rrbracket \sigma \texttt{=} \texttt{frue} \} \end{array}$$

Defining the Collecting Semantics

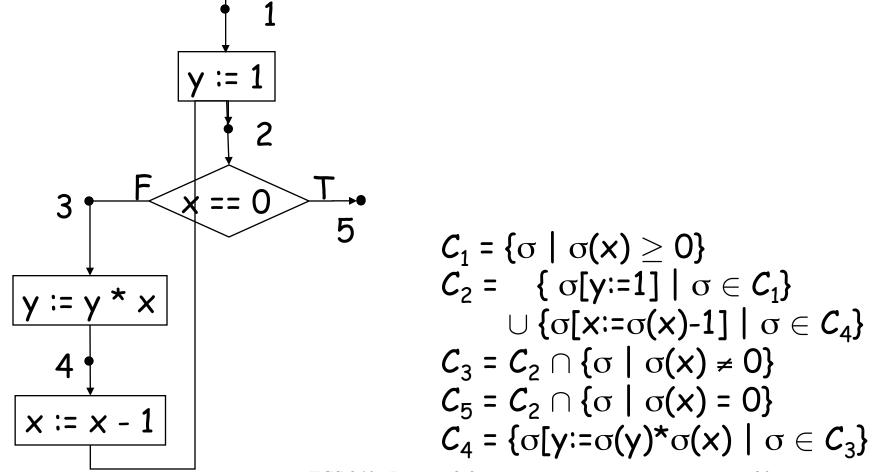
• For a join



$$\textit{C}_{k}$$
 = $\textit{C}_{i} \cup \textit{C}_{j}$

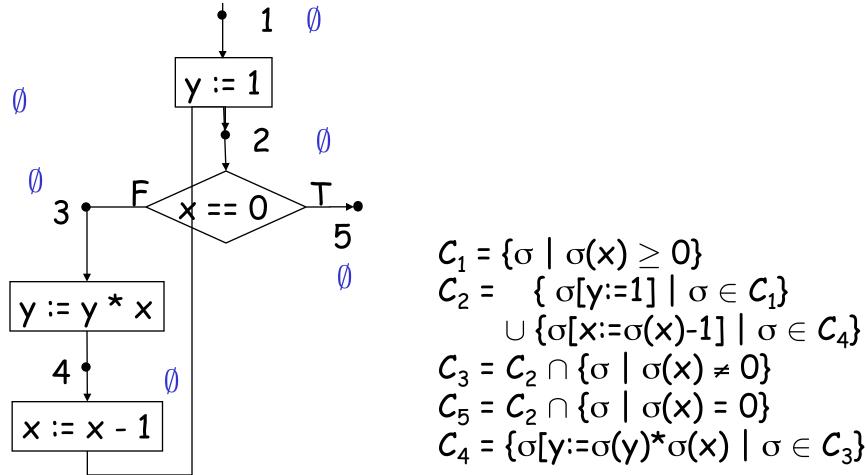
Verify that these relations are monotonic
 If we increase a C_i all other C_j can only increase

• Consider the following program (assume $x \ge 0$ initially)



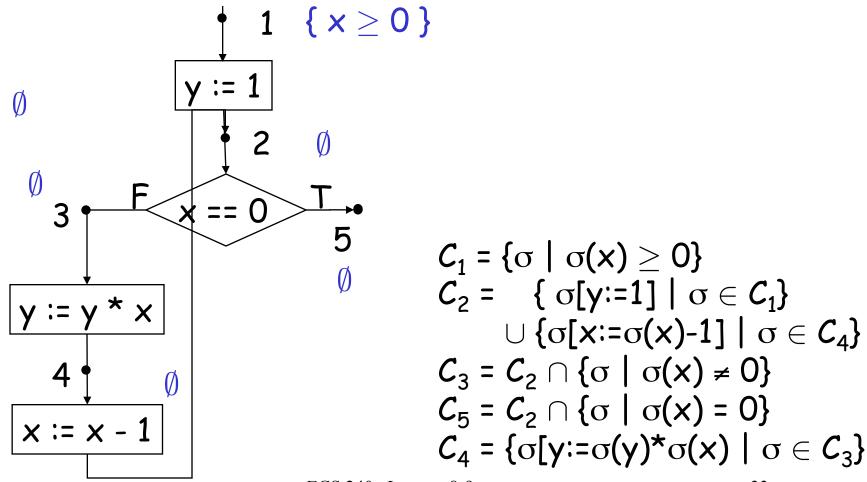
- We have an equation with the unknown C
 - The equation is defined by a monotonic and continuous function on the domain Labels $\rightarrow \mathcal{P}(\Sigma)$
- We can use the least fixed-point theorem
 - We start with $C^0 = \lambda L.\emptyset$
 - We apply the relations between C_i and C_j to construct C_i^1 from C_j^0
 - We stop when $C^{k} = C^{k-1}$
 - The problem is that we'll go on forever for most programs
 - But we know the fixed point exists

• Consider the following program (assume $x \ge 0$ initially)

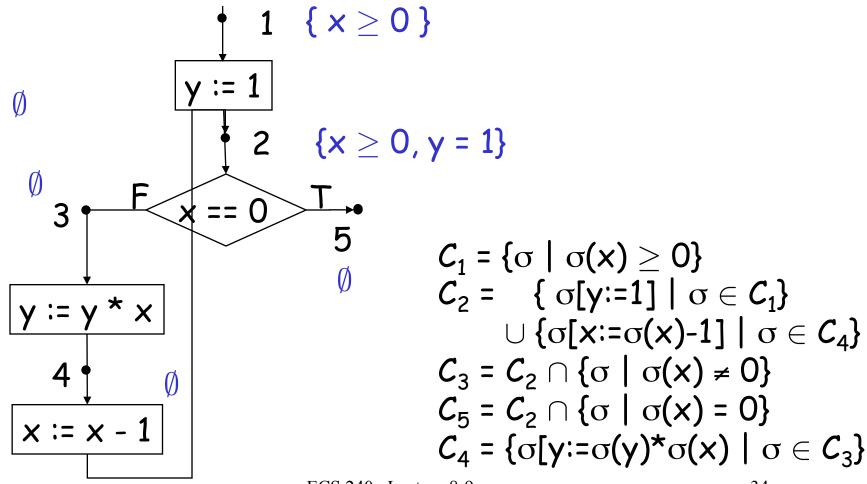


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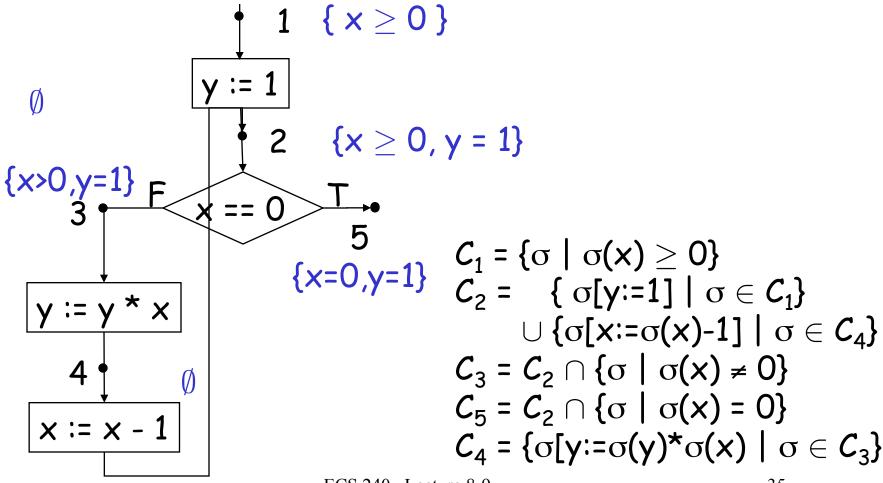
• Consider the following program (assume $x \ge 0$ initially)



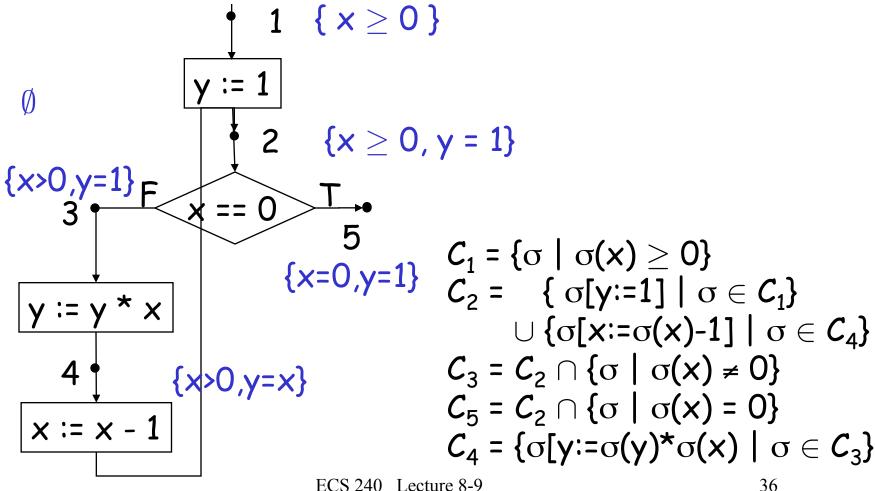
• Consider the following program (assume $x \ge 0$ initially)



• Consider the following program (assume $x \ge 0$ initially)

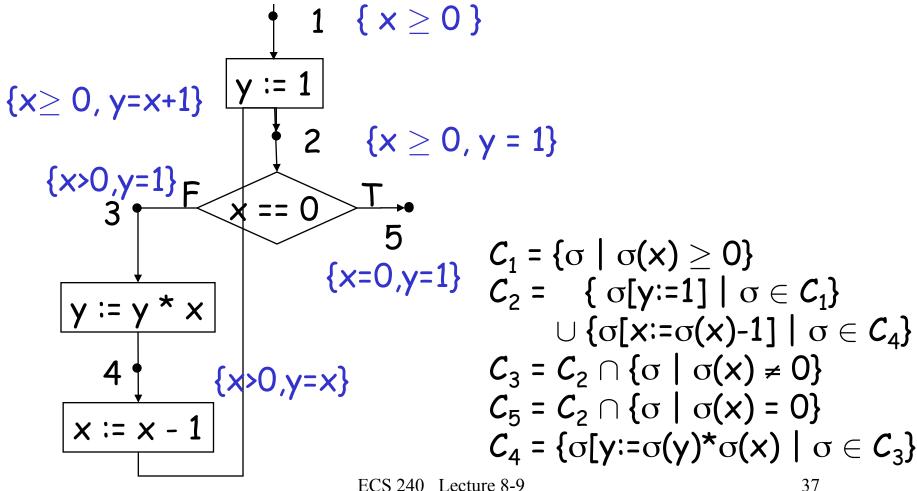


Consider the following program (assume $x \ge 0$ initially)



Collecting Semantics: Example

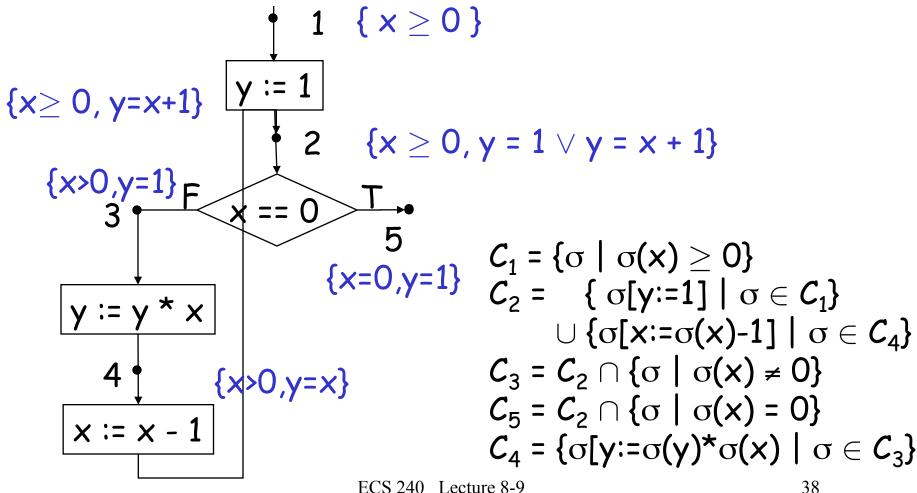
Consider the following program (assume $x \ge 0$ initially)



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Collecting Semantics: Example

Consider the following program (assume $x \ge 0$ initially)



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

 $a \in Labels \rightarrow A$

• Assignment

• Conditional

Concrete:
$$C_j = \{ \sigma \mid \sigma \in C_i \land [\![b]\!]\sigma = false \}$$
 and
 $C_k = \{ \sigma \mid \sigma \in C_i \land [\![b]\!]\sigma = true \}$
Abstract: $a_j = \alpha \{ \sigma \mid \sigma \in \gamma(a_i) \land [\![b]\!]\sigma = false \}$ and
 $a_k = \alpha \{ \sigma \mid \sigma \in \gamma(a_i) \land [\![b]\!]\sigma = true \}$

• Join

Concrete:
$$C_k = C_i \cup C_j$$

Abstract: $a_k = \alpha (\gamma(a_i) \cup \gamma(a_j)) = lub \{a_i, a_j\}$

Least Fixed-Points in the Abstract Domain

- Now we have a recursive equation with unknown "a"
 - Defined by a monotonic and continuous function on the domain Labels \rightarrow A
- We can use the least fixed-point theorem:
 - Start with $a^0 = \lambda L. \perp$
 - Apply the monotonic function to compute a^{k+1} from a^k
 - Stop when $a^{k+1} = a^k$
- Exactly the same computation as for the collecting semantics
 - What is new ?

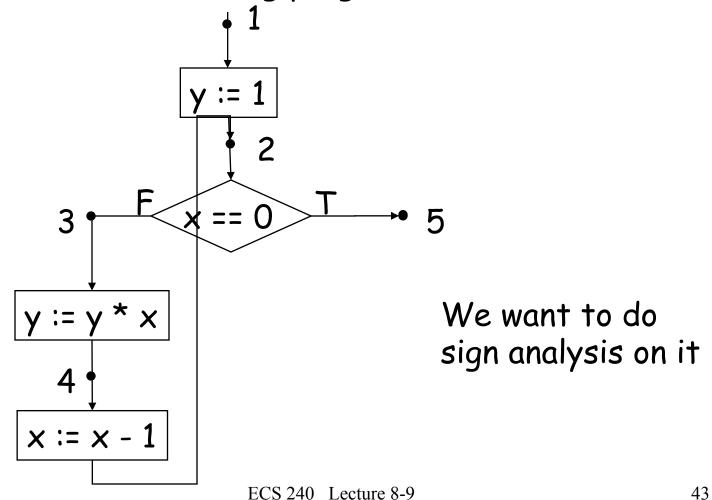
Least Fixed Point in Abstract Domain

- We have a hope of termination
- The classic setup is when A has only uninteresting chains (finite number of elements in each chain)
 - We say that A has finite height (say h)
- In this case the computation takes at most O(h * | Labels|²) steps
 - At each step "a" makes progress on at least one label
 - We can only make progress h times
 - And each time we must compute |Labels| elements
- This is a quadratic analysis: good news

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Abstract Interpretation: Example

Consider the following program



The Abstract Domain for Sign Analysis

• Consider the complete lattice $S = \{ \perp, -, 0, +, \top \}$

- From it construct the complete lattice A = {x, y} \rightarrow S
 - With point-wise ordering as usual
 - The abstract state consists of the sign for x and y

• We start with $a^0 = \lambda L \cdot \lambda v \in \{x, y\}$.

Example

Label		Iterations $ ightarrow$										
1	x	+									+	
	У	\top									\vdash	
2	x		+			Т					\vdash	
	У		+						T		\vdash	
3	x			+			\vdash				\vdash	
	У			+						\vdash	\vdash	
4	x				+			T			\vdash	
	У				+			T			\vdash	
5	x						0				0	
	У						+			Τ	Τ	

Notes

 We abstracted the state of each variable independently

A = {x, y } \rightarrow { \perp , -, 0, +, \top }

- We lost relationships between variables
 - E.g., that at a point x and y are always of the same sign
 - In the previous abstraction we get {x := \top , y := \top } at 2
- We can also abstract the state as a whole

 $A = \mathcal{P}(\{\bot, -, 0, +, \top\} \times \{\bot, -, 0, +, \top\})$

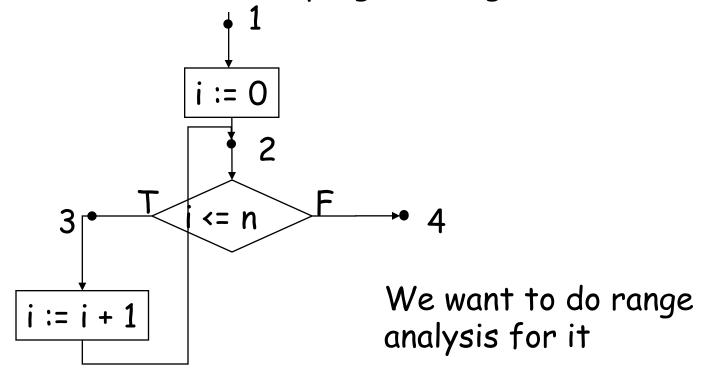
- For the previous example we now get the abstraction $\{(0, +), (+, +)\}$ at 2

Other Abstract Domains

- Range analysis
 - Lattice of ranges: R ={ \perp , [n..m], (- ∞ , m], [n, + ∞), \top }
 - It is a complete lattice
 - [n..m] ⊔ [n' ..m'] = [min(n, n')..ma×(m,m')]
 - [n..m] □ [n' ..m'] = [ma×(n, n')..min(m, m')]
 - + With appropriate care in dealing with ∞
 - $\beta:\mathbb{Z}\to\mathsf{R}$ such that $\beta(\mathsf{n})$ = [n..n]
 - $\alpha : \mathcal{P}(\mathbb{Z}) \to \mathsf{R}$ such that $\alpha(\mathsf{S}) = \mathsf{lub} \{\beta(\mathsf{n}) \mid \mathsf{n} \in \mathsf{S}\} = [\mathsf{min}(\mathsf{S})..\mathsf{max}(\mathsf{S})]$
 - $\gamma : \mathbb{R} \to \mathcal{P}(\mathbb{Z})$ such that $\gamma(r) = \{ n \mid n \in r \}$
- This lattice has infinite-height chains
 - So the abstract interpretation might not terminate !

Example of Non-Termination

• Consider this (common) program fragment



Example of Non-Termination

- Consider the sequence of abstract states at point 2
 - [0..0], [0..1], [0..2], ...
 - The analysis never terminates
 - Or terminates very late if the loop bound is known statically
- It is time to approximate even more: <u>widening</u>
- We redefine the join (lub) operator of the lattice to ensure that from [0..0] upon union with [1..1] the result is [0..+ ∞) and not [0..1]
- Now the sequence of states is
 - [0..0], [0, + ∞), [0, + ∞) Done (no more infinite chains)

- Linear relationships between variables
 - A convex polyhedron is a subset of \mathbb{Z}^k whose elements satisfy a number of inequalities: $a_1 x_1 + a_2 x_2 + ... + a_k x_k \ge c$
 - This is a complete lattice. Use linear programming methods for computing lub
- Linear relationships with at most two variables
 - Like convex polyhedra but with at most two variables per constraint
 - Octagons: $x \pm y \ge c$ have efficient algorithms
- Modulo constraints
 - E.g. even and odd

Summary of Abstract Interpretation

- AI is a very powerful technique that underlies a large number of program analyses
- 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 ECS 240 Lecture 8-9 51