

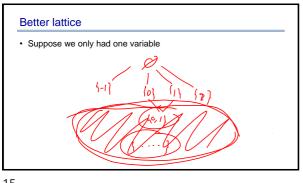
Back to lattice

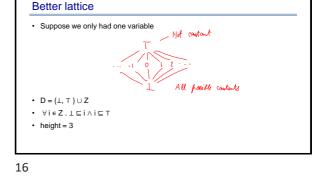
- $\begin{array}{l} \bullet \quad \left(D, \sqsubseteq, \bot, \top, \sqcup, \Pi\right) = \\ \left(2^A, \supseteq, A, \emptyset, \cap, \cup\right) \\ \text{where } A = \left\{ \left. x \to N \mid x \in Vars \land N \in Z \right. \right\} \end{array}$
- · What's the problem with this lattice?

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Back to lattice (D, ⊑, ⊥, T, ⊔, ⊓) = (2^A, ⊇, A, 0, ∩, ∪) where A = { x → N | x ∈ Vars ∧ N ∈ Z } What's the problem with this lattice? Lattice is infinitely high, which means we can't guarantee termination

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For all variables

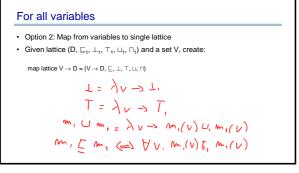
- · Two possibilities
- Option 1: Tuple of lattices
- Given lattices $(D_1, \sqsubseteq_1, \bot_1, \top_1, \sqcup_1, \sqcap_1) \dots (D_n, \sqsubseteq_n, \bot_n, \top_n, \sqcup_n, \sqcap_n)$ create:

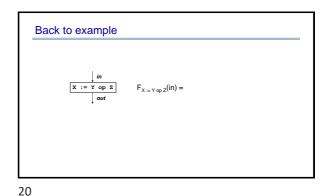
tuple lattice Dn =

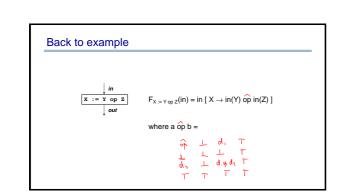
For all variables

- Two possibilities
- Option 1: Tuple of lattices
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\begin{array}{l} \mbox{tuple lattice } D^n=((D_1\times\ldots\times D_n),\sqsubseteq,\bot,\top,\sqcup,\sqcap) \mbox{ where }\\ \bot=(\bot_1,...,\bot_n)\\ \top=(\top_1,...,\top_n)\\ (a_1,...,a_n)\sqcup(b_1,...,b_n)=(a_1\sqcup_1b_1,...,a_n\sqcup_nb_n)\\ (a_1,...,a_n)\sqcup(b_1,...,b_n)=(a_1\sqcap_1b_1,...,a_n\sqcup_nb_n)\\ (a_1,...,a_n)\sqcap(D_1,...,b_n)=(a_1\sqcap_1b_1,...,a_n\sqcup_nb_n)\\ \mbox{height}=\mbox{height}(D_1)+...+\mbox{height}(D_n) \end{array}
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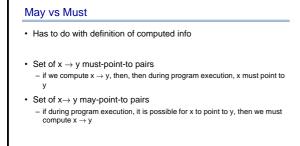


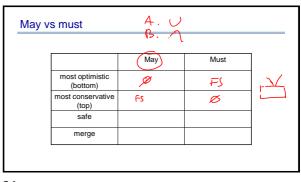


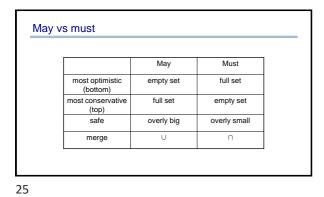


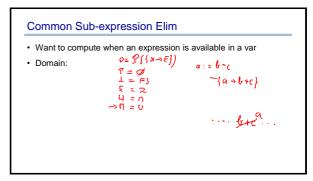
- · Simple lattices:
 - boolean logic lattice
 - powerset lattice
 - incomparable set: set of incomparable values, plus top and bottom (eg const prop lattice)
 - two point lattice: just top and bottom
- · Use combinators to create more complicated lattices
 - tuple lattice constructor
 - map lattice constructor

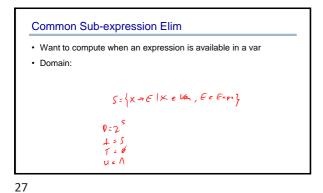
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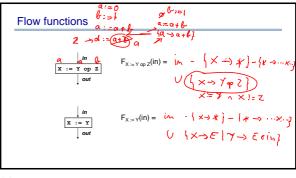


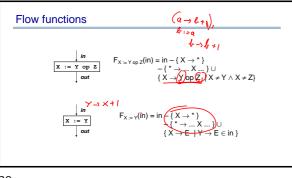


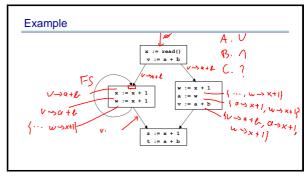












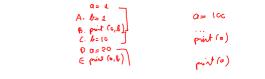
Direction of analysis

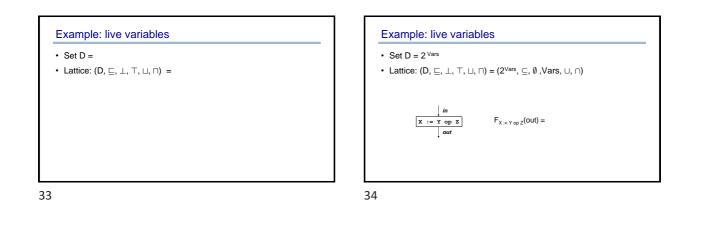
- Although constraints are not directional, flow functions are
- All flow functions we have seen so far are in the forward direction
- In some cases, the constraints are of the form $\label{eq:interm} \mbox{in} = F(\mbox{out})$
- · These are called backward problems.
- Example: live variables
 compute the set of variables that may be live

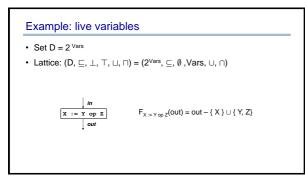
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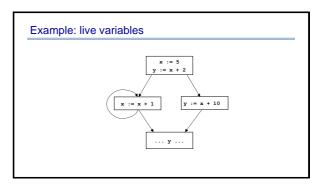
Live Variables

- A variable is live at a program point if it will be used before being redefined
- A variable is dead at a program point if it is redefined before being used

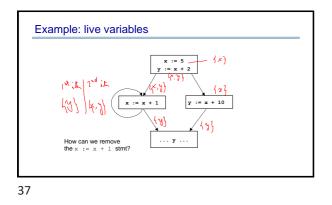


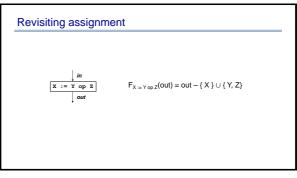


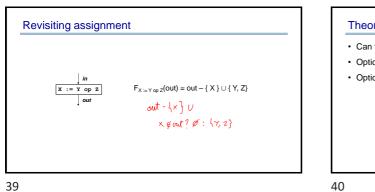








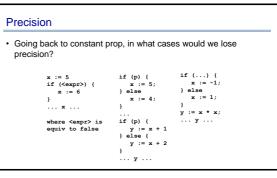






- · Can formalize backward analyses in two ways
- Option 1: reverse flow graph, and then run forward problem
- · Option 2: re-develop the theory, but in the backward direction

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Precision

· Going back to constant prop, in what cases would we lose precision?

Precision

- · The first problem: Unreachable code
 - solution: run unreachable code removal before
 the unreachable code removal analysis will do its best, but may not
 - remove all unreachable code removal analysis will do its best, but may no remove all unreachable code
- · The other two problems are path-sensitivity issues
 - Branch correlations: some paths are infeasible
 - Path merging: can lead to loss of precision

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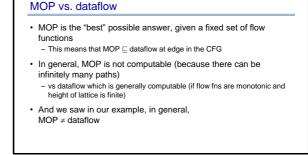
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MOP: meet over all paths

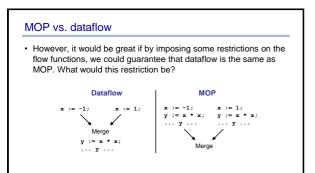
Information computed at a given point is the meet of the information computed by each path to the program point



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MOP vs. dataflow

- However, it would be great if by imposing some restrictions on the flow functions, we could guarantee that dataflow is the same as MOP. What would this restriction be?
- · Distributive problems. A problem is distributive if:

 $\forall a, b . F(a \sqcup b) = F(a) \sqcup F(b)$

· If flow function is distributive, then MOP = dataflow

Summary of precision

- · Dataflow is the basic algorithm
- To basic dataflow, we can add path-separation

 - Get MOP, which is same as dataflow for distributive problems
 Variety of research efforts to get closer to MOP for non-distributive problems
- · To basic dataflow, we can add path-pruning - Get branch correlation
- To basic dataflow, can add both: meet over all feasible paths