

Dataflow Frameworks, conclusion

Announcements

- Homework is due Monday
 - Problem 6(b) is Extra credit
 - Submit in Submitty
 - You can lock your team later. Maximal size is 3. Ideal size is 2.
- Quiz 1 today

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Outline of Today's Class

- Dataflow frameworks, conclusion
- MOP solution vs. MFP solution
- Non-distributive analyses
 - Constant propagation

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Monotone Dataflow Frameworks

- A problem fits into the dataflow framework if
 - its property space is a lattice L, \leq that satisfies the *Ascending Chain Condition*
 - its merge operator V is the join of Land
 - its transfer function space $F: L \rightarrow L$ is monotone
- Thus, we can make use of a generic solution procedure, known as the worklist algorithm or the maximal fixpoint algorithm or the fixpoint iteration algorithm

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Catch up: Transfer Functions

- **The transfer functions: $f: L \rightarrow L$.** Formally, function space F is such that
 1. F contains all f_j
 2. F contains the identity function $\text{id}(x) = x$
 3. F is closed under composition
 4. **Each f is monotone**

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Catch up: Monotonicity

- $F: L \rightarrow L$ is **monotone** if and only if:
 - (1) a, b in L , f in F then $a \leq b \implies f(a) \leq f(b)$
 - or (equivalently):
 - (2) x, y in L , f in F then $f(x) \vee f(y) \leq f(x \vee y)$
- Theorem: Definitions (1) and (2) are equivalent.
 - Show that (1) implies (2)
 - Show that (2) implies (1)

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Catch up: Distributivity

- $F: L \rightarrow L$ is **distributive** if and only if x, y in L , f in F then $f(x \vee y) = f(x) \vee f(y)$
- Every distributive function is also monotone but not the other way around
- Distributivity is a very nice property!

Catch up: Monotonicity and Distributivity

- Is classical *Reach* distributive?
 - Yes
 - To show distributivity:
For each j $((X \cup Y) \cap \text{pres}(j)) \cup \text{gen}(j) = ((X \cap \text{pres}(j)) \cup \text{gen}(j)) \cup ((Y \cap \text{pres}(j)) \cup \text{gen}(j))$
- $$((X \cup Y) \cap \text{pres}(j)) \cup \text{gen}(j) = ((X \cap \text{pres}(j)) \cup (Y \cap \text{pres}(j))) \cup \text{gen}(j) = ((X \cap \text{pres}(j)) \cup \text{gen}(j)) \cup ((Y \cap \text{pres}(j)) \cup \text{gen}(j))$$

Monotone Dataflow Frameworks

- A problem fits into the dataflow framework if
 - its property space is a lattice L, \leq that satisfies the *Ascending Chain Condition*
 - its merge operator \vee is the join of L and
 - its transfer function space $F: L \rightarrow L$ is monotone
- Thus, we can make use of a generic solution procedure, known as the **worklist algorithm** or the **maximal fixpoint algorithm** or the **fixpoint iteration algorithm**

Worklist Algorithm for Forward Dataflow Problems

```

/* Initialize to initial values; 1 is entry node of CFG */
in(1) = InitialValue;      in_Reach(1) = UNDEF
for m = 2 to n do in(m) = 0; in_Reach(m) = {}
W = {1,2,...,n} /* put every node on the worklist */

while W ≠ ∅ do {
  remove j from W
  out(j) = f_j(in(j))
  for i in successors(j)
    if out(j) ≰ in(i) then {
      in(i) = out(j) ∨ in(i)
      W = W ∪ {i}
    }
  out_Reach(j) = (in_Reach(j) ∩ pres(j)) ∪ gen(j)
  if out_Reach(j) ≰ in_Reach(i)
    in_Reach(i) = out_Reach(j) ∪ in_Reach(i)
}

```

Worklist Algorithm for Forward Dataflow Problems (slightly different)

```

/* Initialize to initial values; 1 is entry node of CFG */
in(1) = InitialValue; out(1) = f_1(in(1))
for m = 2 to n do in(m) = 0; out(m) = f_m(0)
W = {2,...,n} /* put every node but 1 on the worklist */

while W ≠ ∅ do {
  remove j from W
  in(j) = ∨ { out(i) | i is predecessor of j }
  out(j) = f_j(in(j))
  if out(j) changed then
    W = W ∪ { k | k is successor of j }
}

```

Termination Argument

- Why does the algorithm terminate?
- Sketch of argument:
At each "phase", at least one $out(j)$ changes. Monotonicity of f_j entails that change of i is up the chain: $out'(j) \geq out(j)$. Since $out(j)$ in L , and L satisfies the *Ascending Chain Condition*, $out(j)$ changes at most $O(h)$ times where h is the height of the lattice L .

Correctness Argument

- Theorem: The worklist algorithm computes a solution that satisfies the dataflow equations
- Why?
- Sketch of argument:

Whenever j is processed, algorithm sets $out(j) = f_j(in(j))$. Whenever $out(j)$ changes, algorithm puts successors on the list, so $in(j) = \mathbf{V} \{ out(i) \}$.

So final solution will satisfy equations.

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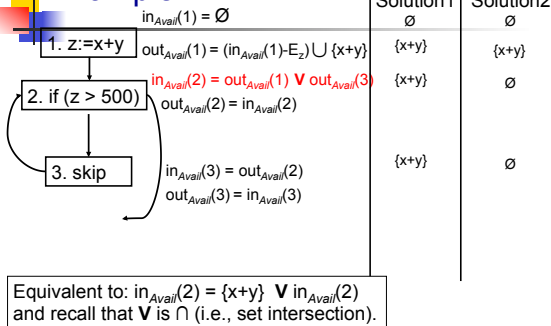
Precision Argument

- Theorem: The algorithm computes the **least solution** of the dataflow equations.
 - Historically though, this solution is called the **maximal fixpoint solution (MFP)**
 - I.e., For every node j , the worklist algorithm computes a solution $\mathbf{MFP}(j) = \{in(j), out(j)\}$, such that every other solution $\{in'(j), out'(j)\}$ of the dataflow equations is $in(j) \leq in'(j)$, $out(j) \leq out'(j)$

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Example



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Question

Willy Wazoo changed the worklist algorithm to initialize to 1.

```

/* Initialize to initial values; 1 is entry node of CFG */
in(1) = InitialValue;      in_Reach(1) = UNDEF
for m = 2 to n do in(m) = 1  in_Reach(m) = ALL_DEFS
W = {1, 2, ..., n} /* put every node on the worklist */

while W ≠ ∅ do {
  remove j from W
  out(j) = f_j(in(j))
  for i in successors(j)
    if out(j) ≰ in(i) then {
      in(i) = out(j) V in(i)
      W = W U { i }
    }
  out_Reach(j) = (in_Reach(j) ∩ pres(j)) U gen(j)
  if out_Reach(j) ≰ in_Reach(i)
    in_Reach(i) = out_Reach(j) U in_Reach(i)
}
    
```

1. Does Willy's algorithm compute an over-approximation or an under-approximation of the MFP?

Meet Over All Paths (MOP)

-
- Desired dataflow information at n is obtained by traversing ALL PATHS from 1 (entry node) to n . For every path $p = (1, n_2, n_3, \dots, n_k)$ we compute $f_{n_k}(\dots f_{n_2}(f_1(\text{init}(1))))$
 - The MOP at entry of n is $\mathbf{V} f_{n_k}(\dots f_{n_2}(f_1(\text{init}(1))))$ over all paths p from 1 to n

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MOP vs. MFP

- The MOP is an abstract model for the best solution computable with this kind of static analysis
 - It is a common assumption in this kind of static analysis that *all program paths are executable*
 - (Abstract interpretation and axiomatic semantics abstract state more precisely, and can rule out some paths)
- The MFP is the solution computed by the worklist algorithm

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MOP vs. MFP

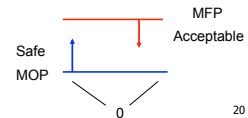
- For *distributive* problems **MFP = MOP!**
- Unfortunately, for *monotone* problems this is not true. But we still have a **safe** solution: it is a theorem that for monotone problems, **MFP \geq MOP**

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Safety of a Dataflow Solution

- A **safe** (also, **correct** or **sound**) solution X **overestimates** the “best” possible dataflow solution, i.e., $X \geq \text{MOP}$
- Historically, an **acceptable** solution X is one that is better than what we can do with the MFP, i.e., $X \leq \text{MFP}$



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Safe Solutions

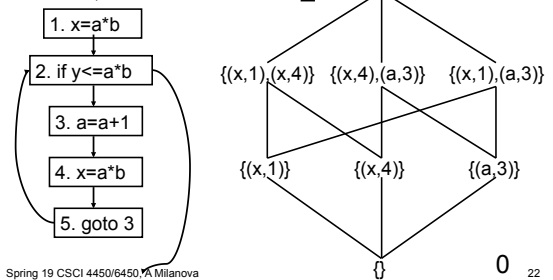
- In *many* problems 1 is the universal set of facts, the merge operator is set union. It is **safe** to err by saying that a fact reaches a node when in fact it doesn't
- E.g., intuitively, it is **safe** to err by saying that a definition (x,k) reaches a node, when in fact it **MAY NOT REACH** that node
- Safe** entails “larger” than the MOP under our partial order. Our definition of \leq is subset inclusion (which is natural). So “safer” solutions are larger sets

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Safe Solutions: Reach

$U =$ all definitions: $\{(x,1), (x,4), (a,3)\}$ 1
Poset is 2^U , \leq is the subset relation \subseteq



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Safe Solutions

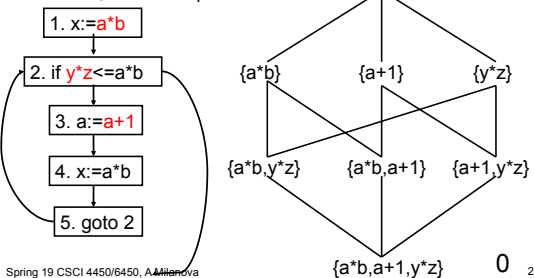
- In *most* problems the 1 is the empty set, and the merge operator is set intersection. It is **safe** to err by saying that a fact does not reach a node when in fact it does
- E.g., intuitively, it is **safe** to err by saying that an expression is **NOT AVAILABLE** when in fact it may be available
- Safe** means larger than the MOP under our partial order. Under our definition of \leq , which is superset, “safer” solutions end up being smaller sets

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Safe Solutions: Avail

$U =$ all expressions: $\{a*b, a+1, y*z\}$ 1
Poset is 2^U , \leq is the superset relation \supseteq



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Precision of a Dataflow Solution

- **Precise** solution is one that is “close” to MOP
 - A precise solution contains few spurious dataflow facts (spurious facts is what we call **noise**)
 - Unfortunately, for most problems even the MOP (an approximation itself!) is undecidable
- $MOP \leq X \leq Y$: X is more precise than Y
 - Usually we can compare two solutions X and Y
 - But, for most problems, we have no way of knowing the “ground truth”

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Outline of Today's Class

- Dataflow frameworks
- MOP vs. MPF
- **Non-distributive analyses**
 - Constant propagation

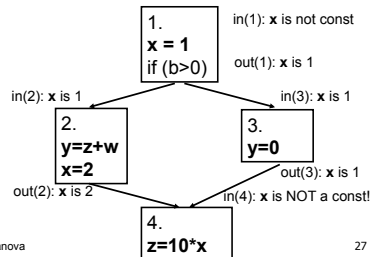
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Constant Propagation (Simple)

- Problem statement: What variables always hold constant values at a given program point

- Example:



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Aside: Defining an Analysis

- Define program syntax
 - In practice, we deal with a lot more than the simple abstraction ☺
- Define property space
 - The *abstract program state* that approximates the concrete program state
- Define transfer function space over syntax
 - Symbolically execute program over abstract state

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Aside: Defining an Analysis

- If property space has desired properties
 - is a lattice L, \leq that satisfies the *Ascending Chain Condition*
 - merge operator V is the join of L and
- Function space $F: L \rightarrow L$ is monotone then analysis fits the monotone dataflow framework and can be solved using the worklist algorithm

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Constant Propagation: Syntax

$S ::= S; S \mid \text{while } (b) \{ S \} \mid \text{if } (b) \{ S \} \text{ else } \{ S \}$
 $\mid x = V \mid x = V \text{ Op } V$

$Op ::= + \mid - \mid * \mid /$

$V ::= x \mid y \mid z \mid C$

- x, y, z are program variables
- C is constant
- We have to define transfer functions for $x = V$ and $x = V \text{ Op } V$

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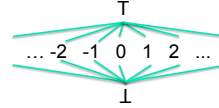
Constant Propagation: Property Space

- Associate one of the following values with variable x at each program point

value	meaning
1 (or T)	x is NOT a constant
c	x has constant value c
0 (or \perp)	x is unknown

Constant Propagation: Lattice

- Lattice L_x, \leq



- Dataflow lattice L is the product of L_x
 - I_1, I_2 in L , $I_1 \leq I_2$ iff $I_{1,x} \leq I_{2,x}$ for every variable x
 - $I_1 \vee I_2$ amounts to $I_{1,x} \vee I_{2,x}$ for every variable x
 - Merge operator is join of L
- Does the product lattice satisfy the ACC?

Constant Propagation: Transfer Functions

- $j: x = c$
 f_j : kill $x \rightarrow \text{val}$, generate $x \rightarrow c$
- $j: x = y$
 f_j : kill $x \rightarrow \text{val}$, add $x \rightarrow \text{val}'$, s.t. $y \rightarrow \text{val}'$ in $\text{in}(j)$.
- val and val' are one of
 - \perp : bottom (unknown)
 - c : constant
 - T : top (not a constant)

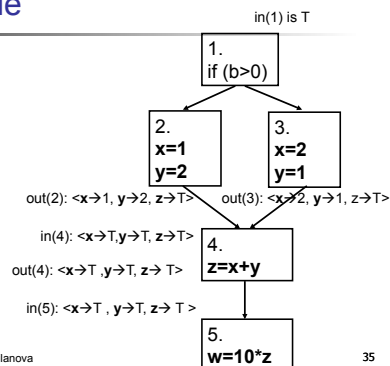
Constant Propagation: Transfer Functions

- $j: x = V_1 \text{ Op } V_2$
 f_j : kill: $x \rightarrow \text{val}$
 gen:

If $V_1 \rightarrow c_1$ and $V_2 \rightarrow c_2$ in $\text{in}(j)$, then $x \rightarrow c_1 \text{ Op } c_2$
 else if $V_1 \rightarrow T$ or $V_2 \rightarrow T$ in $\text{in}(j)$, then $x \rightarrow T$
 else $x \rightarrow \perp$

- Next, we'll argue monotonicity which would give us that Constant Propagation is solvable by the Worklist algorithm

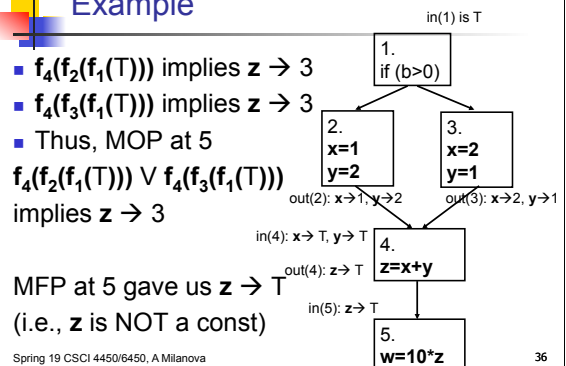
Example



Not Distributive! A Counter Example

- $f_4(f_2(f_1(T)))$ implies $z \rightarrow 3$
- $f_4(f_3(f_1(T)))$ implies $z \rightarrow 3$
- Thus, MOP at 5
- $f_4(f_2(f_1(T))) \vee f_4(f_3(f_1(T)))$ implies $z \rightarrow 3$

MFP at 5 gave us $z \rightarrow T$
 (i.e., z is NOT a const)





Next Class

- We'll continue with non-distributive analyses
 - Constant propagation
 - Points-to analysis

- Introduction to Soot