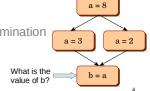
## **Data Flow Analysis**

#### Rupesh Nasre.

CS6843 Program Analysis IIT Madras Jan 2015

### **Data Flow Analysis**

- Flow-sensitive: Considers the control-flow in a function
- Operates on a flow-graph with nodes as basicblocks and edges as the control-flow
- Examples
  - Constant propagation
  - Common subexpression elimination
  - Dead code elimination



#### **Outline**

- · What is DFA?
  - Reaching definitions
  - Live variables
- DFA framework
  - Monotonicity
  - Confluence operator
  - MFP/MOP solution
- · Analysis dimensions

**Reaching Definitions** 

- · Every assignment is a definition
- A definition d reaches a program point p if there exists a path from the point immediately following d to p such that d is not killed along the path.

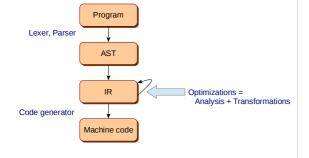
B1 D3: x = 1D5: y = 3D1: x = 10D2: y = 11if c

D5: z = xD6: z = xD6: z = 4B2
B3

What definitions reach B3?

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# **Compiler Organization**

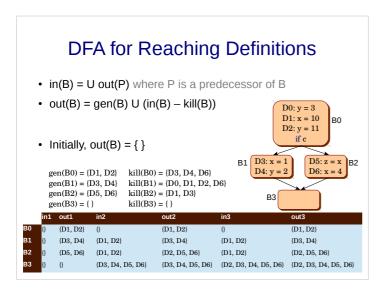


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## **DFA Equations**

- in(B) = set of data flow facts entering block B
- out(B) = ...
- gen(B) = set of data flow facts generated in B
- kill(B) = set of data flow facts from the other blocks killed in B

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## **DFA for Reaching Definitions**

Domain	Sets of definitions			
Transfer function	$\begin{split} ∈(B) = U \ out(P) \\ &out(B) = gen(B) \ U \ (in(B) - kill(B)) \end{split}$			
Direction	Forward			
Meet / confluence operator	U			
Initialization	out(B) = { }			

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# Algorithm for Reaching Definitions

#### for each basic block B

compute gen(B) and kill(B)
out(B) = {}

Can you do better? Hint: Worklist

#### do {

#### for each basic block B

in(B) = U out(P) where P in pred(B)out(B) = gen(B) U (in(B) - kill(B))

} while in(B) changes for any basic block B<sub>8</sub>

Classwork

#### **DFA for Live Variables**

Domain	Sets of variables				
Transfer function	$\begin{split} ∈(B) = use(B) \ U \ (out(B) - def(B)) \\ &out(B) = U \ in(S) \ where \ S \ is \ a \ successor \ of \ B \end{split}$				
Direction	Backward				
Meet / confluence operator	U				
Initialization	in(B) = { }				

A variable v is live at a program point p if v is used along some path in the flow graph starting at p. Otherwise, the variable v is dead.

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# in(B) = U out(P) where P is a predecessor of B out(B) = gen(B) U (in(B) - kill(B)) D1: y = D2: x =

Initially, out(B) = { }

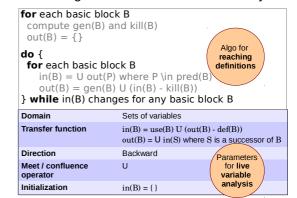
 $\begin{array}{lll} gen(B0) = \{D1,\,D2\} & & kill(B0) = \{D3,\,D4,\,D6,\,D8\} \\ gen(B1) = \{D3,\,D4\} & & kill(B1) = \{D1,\,D2,\,D6,\,D8\} \\ gen(B2) = \{D5,\,D6\} & & kill(B2) = \{D2,\,D3,\,D7,\,D8\} \\ gen(B3) = \{D7,\,D8\} & & kill(B3) = \{D2,\,D3,\,D5,\,D6\} \end{array}$ 

3301 01 0	
D1: y = 3 D2: x = 10 if c B1 D3: x = 1 D5: z = x	
B1 $D3: x = 1$ D4: y = 2 $D5: z = xD6: x = 4$	
B3 D7: z = y D8: x = z	

	in1	out1	in2	out2	in3	out3	in4	out4
B0	{}	{D1, D2}	{D7, D8}	{D1, D2, D7}	{D4, D7, D8}	{D1, D2, D7}	{D1,4,7}	{D1,2,7}
B1	{}	$\{\mathrm{D3},\mathrm{D4}\}$	{D1, D2}	{D3, D4}	{D1, D2, D7}	{D3, D4, D7}	{D1,2,7}	{D3,4,7}
B2	{}	$\{\mathrm{D5},\mathrm{D6}\}$	{D1, D2}	{D1, D5, D6}	{D1, D2, D7}	{D1, D5, D6}	{D1,2,7}	{D1,5,6}
В3	{}	{D7, D8}	(D3, D4, D5, D6)	{D4, D7, D8}	{D1, D3, D4, D5,	{D1, D4, D7, D8}	{D1,3,4,5,6,7}	{D1,4,7,8}
					D6}			

#### Classwork

· Write an algorithm for Live Variable Analysis



#### **Direction and Confluence**



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#### Monotone Framework

• A framework < $\mathcal{L}$ ,  $\Pi$ ,  $\mathcal{F}$ > is monotone if  $\mathcal{F}$  is monotonic, i.e.,

 $(\forall f \in F)(\forall x, y \in L), x \ge y \Rightarrow f(x) \ge f(y)$ 

• If a data-flow framework is monotonic, the convergence (termination) is guaranteed for finite height lattices.

#### **Data Flow Framework**

- · Point: start or end of a basic block
- · Information flow direction: forward / backward
- · Transfer functions
- Meet / confluence operator
- One can define a transfer function over a path in the CFG  $f_k(f_{k,1}(...f_0(f_1(f_0(T))...))$  // small k (block)
- $MOP(x) = \prod f_v(T)$   $K \in Paths(x)$ // capital K Meet over all paths Path enumeration is expensive

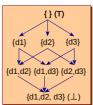
## Distributive Framework

- A framework < L,  $\Pi$ ,  $\mathcal{F}>$  is distributive if  $\mathcal{F}$  is distributive, i.e.,  $(\forall f \in F)(\forall x, y \in L) f(x \sqcap y) \le f(x) \sqcap f(y)$
- · Maximal fixed point (MFP) solution is obtained with our iterative DFA.
- · MFP is unique and order independent.
- The best we can do is MOP (most feasible, but undecidable).
- In general, MFP  $\leq$  MOP  $\leq$  Perfect solution.
- If distributive, MFP = MOP.
- Every distributive function is also monotonic.

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#### Structure in Data Flow Framework

- A semilattice  $\mathcal{L}$  with a binary meet operator  $\Pi$ , such that a, b,  $c \in \mathcal{L}$ 
  - Idempotency:  $a \Pi a = a$
  - Commutativity:  $a \Pi b = b \Pi a$
  - Associativity:  $a \Pi (b \Pi c) = (a \Pi b) \Pi c$
- $\Pi$  imposes an order on  $\mathcal{L}$ 
  - a >= b ⇔ a П b = b
- $\mathcal{L}$  has a bottom element  $\perp$ , a  $\Pi \perp = \perp$
- $\mathcal{L}$  has a top element T, a  $\Pi$  T = a



Reaching Definitions Lattice

# **Outline**

- · What is DFA?
  - Reaching definitions
  - Live variables
- · DFA framework
  - Monotonicity
  - Confluence operator
  - MFP/MOP solution
- · Analysis dimensions

How many ancestor names do you need to almost uniquely identify a student in campus?

## **Analysis Dimensions**

An analysis's precision and efficiency is guided by various design decisions.

- · Flow-sensitivity
- · Context-sensitivity
- · Path-sensitivity
- · Field-sensitivity



How many hands are required to know the time precisely?

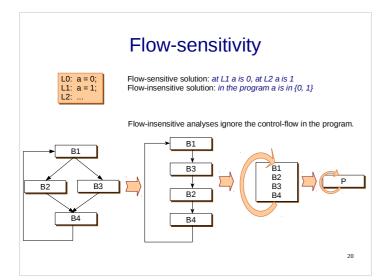
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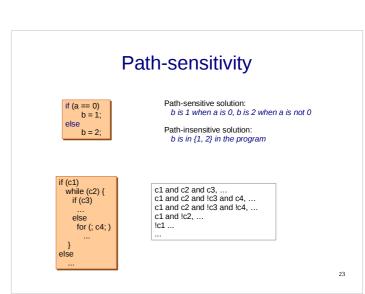
# Context-sensitivity

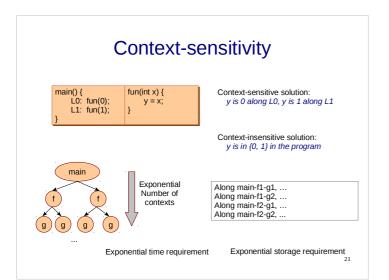
main() {
 L0: fun(0);
 L1: fun(1);
}
fun(int x) {
 y = x;
}

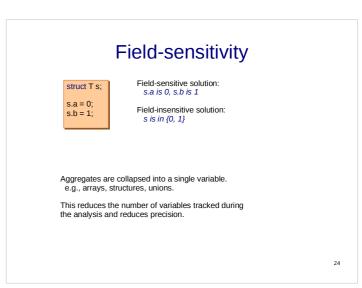
Context-sensitive solution: y is 0 along L0, y is 1 along L1

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#### A Note on Abstraction

Maintain one bit for x == 0Initialized to F (false)

> F x = 0; T ++x; F --x;

> > 25

#### **Conservative Analysis**

- · Being safe versus being precise
  - Relation with lattice
  - Initializations and confluence
  - Constructive versus destructive operators
- · Safety versus liveness property
  - Absence of bugs versus presence of a bug

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#### A Note on Choosing Abstraction

Maintain one bit for x == 0Initialized to F (false)

F x = 0; T ++x; F --x;  $\begin{array}{c} \text{Maintain two bits for value of x} \\ \text{Initialized to } \begin{array}{c} \text{OO} \end{array}$ 

00 x = 0; 00 ++x; 01 --x; 00 Maintain one bit for x == 0
Another bit for x < 2
Initialized to 00

00 x = 0; 11 ++x; 01 --x; 11

If type information available, then {01} --x {11} possible. Otherwise, {01} --x {00}

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#### Soundness and Precision

- · Analyses enable optimizations.
- An optimization is sound if it maintains the functionality of the original code.
- A program may be optimized in certain scenarios.
- An analysis is sound if it leads to sound optimization.
  - The analysis does not enable optimization outside the above set of scenarios.
- An analysis is complete if it does not disable optimization for any possible scenario.

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Sound)

Scenarios

Complete

# **Abstraction Storage**

- · Saturating counters
- Number of values stored faithfully with log(n) bits – (n-2)
- Additional information may help increase the range, e.g., type information as unsigned.

On Soundness

- Usually, multiple optimizations expect same information-theoretic behavior from analyses.
  - If more information means analysis A1 is less precise according to optimization O1, often optimization O2 also sees A1 that way.
  - This allows us to argue about analysis soundness without talking about optimizations.
- But this is not always true.
  - Soundness depends upon optimization enabling.
  - And two opposite optimizations may see the information from the same analysis in opposing ways.

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## **Optimization-specific Soundness**

- Consider O1 that changes \*p to x if p points to only x.
- Consider O2 that makes p volatile if p points to multiple variables at different program points.
- Analysis A computes points-to information  $p \rightarrow \{x, y\}$ 
  - If A computes more information  $p \rightarrow \{x, y, z\}$ , O1 is suppressed but O2 is enabled.
  - If A computes less information p → {x}, O1 is enabled and O2 is suppressed.
  - Thus, conservative for one is precise for another.
  - And sound for one is unsound for another.

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# Optimization-specific Soundness

- Consider O1 that converts multiplication by 2 to a leftbit-shift operation (x \* 2 to x << 1).
- Consider O2 that uses a special circuit (fast operation) when there is a sum of reciprocals of powers of 2 (1 + ½ + ¼ + ...)
- Analysis A is used to compute values of arithmetic expressions.
  - Converting 1.98 to 2 enables O1, disables O2.
  - Converting 1.98 to 1.96875 enables O2, disables O1.
  - Precise for one is imprecise for another.
  - Sound for one is unsound for another.

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# Acknowledgements

#### Course notes from

- · Katheryn McKinley
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