

Data Flow Analysis

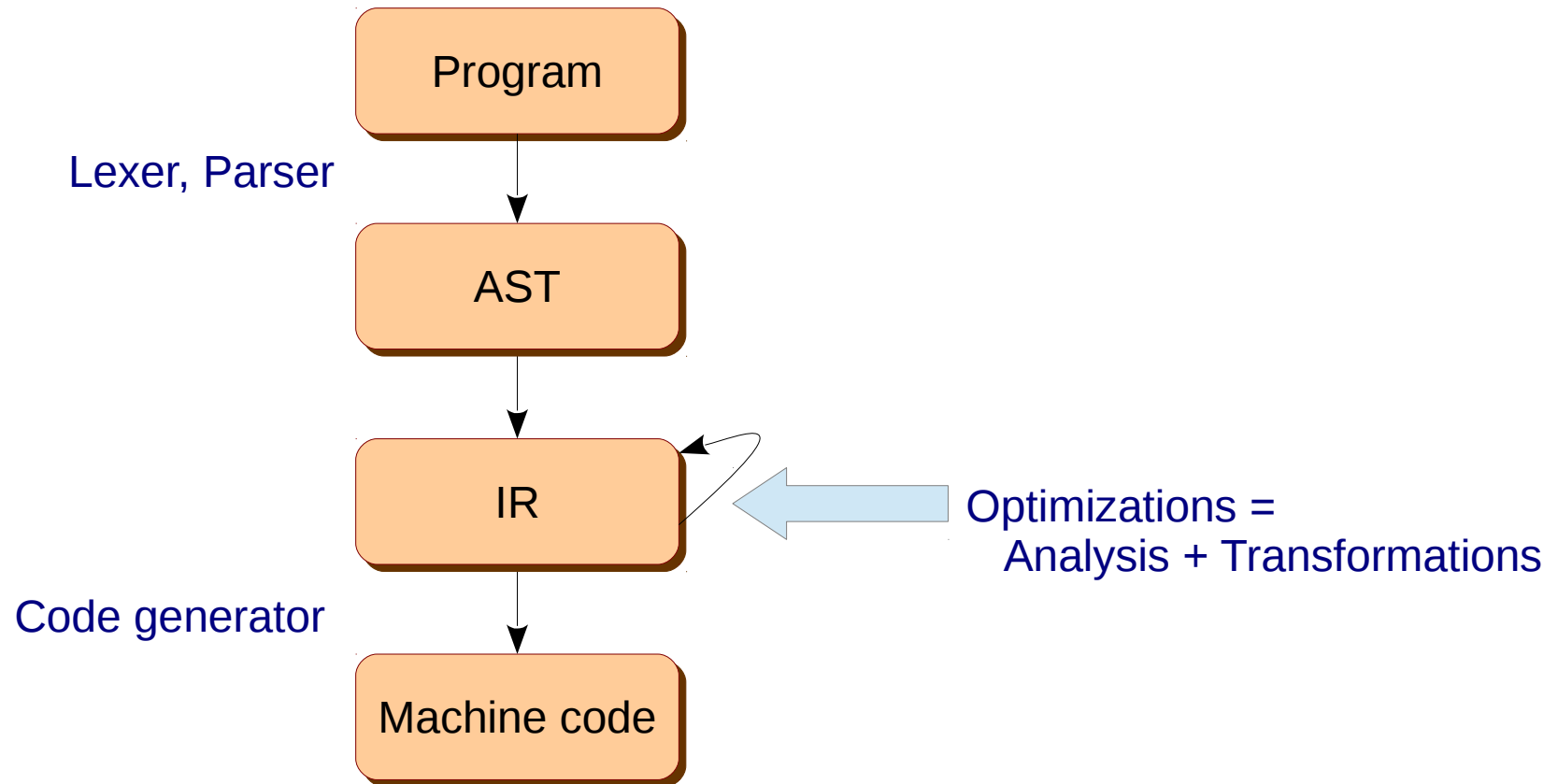
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CS6843 Program Analysis
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Outline

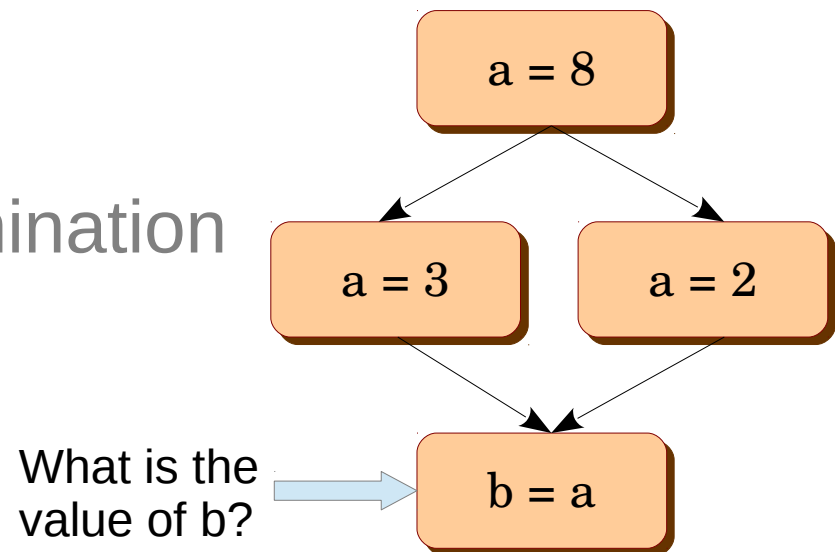
- What is DFA?
 - Reaching definitions
 - Live variables
- DFA framework
 - Monotonicity
 - Confluence operator
 - MFP/MOP solution
- Analysis dimensions

Compiler Organization



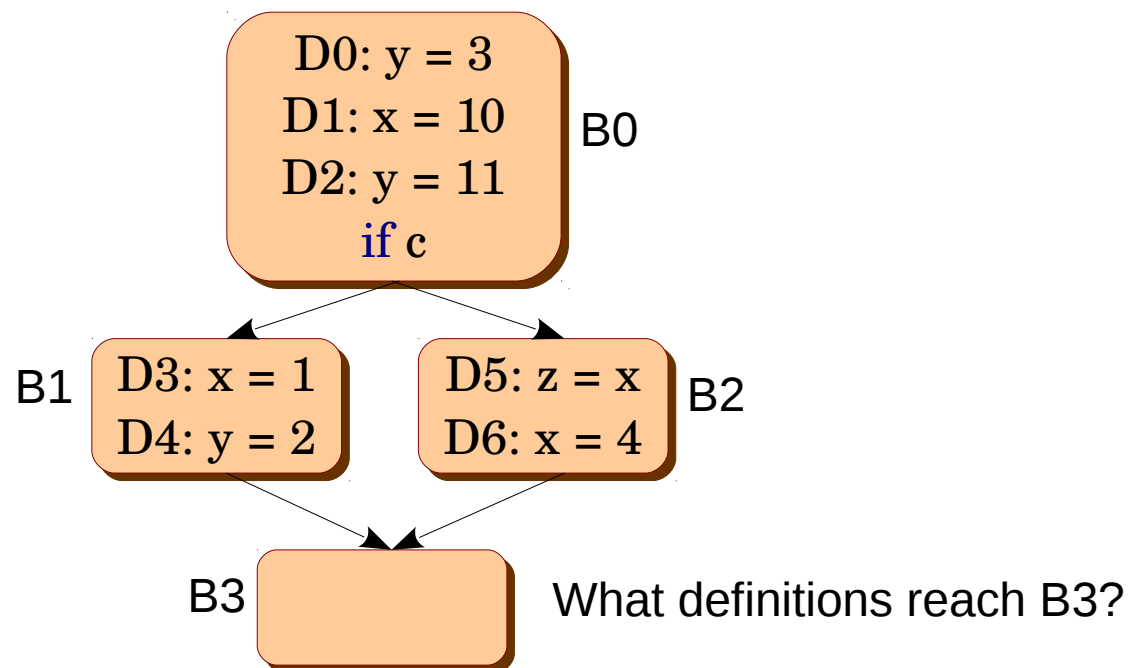
Data Flow Analysis

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



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.



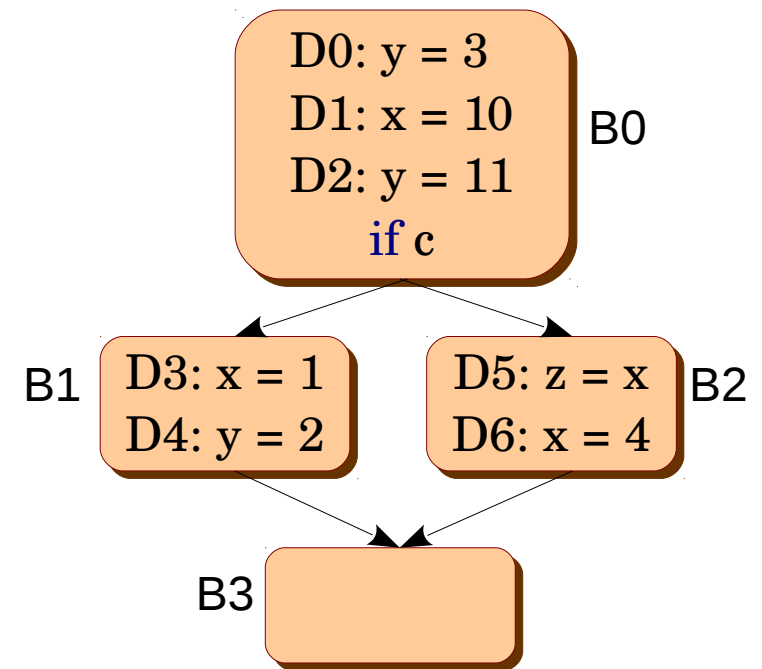
DFA Equations

- $\text{in}(B)$ = set of data flow facts entering block B
- $\text{out}(B) = \dots$
- $\text{gen}(B)$ = set of data flow facts generated in B
- $\text{kill}(B)$ = set of data flow facts from the other blocks killed in B

DFA for Reaching Definitions

- $in(B) = \cup out(P)$ where P is a predecessor of B
- $out(B) = gen(B) \cup (in(B) - kill(B))$
- Initially, $out(B) = \{ \}$

$gen(B0) = \{D1, D2\}$ $kill(B0) = \{D3, D4, D6\}$
 $gen(B1) = \{D3, D4\}$ $kill(B1) = \{D0, D1, D2, D6\}$
 $gen(B2) = \{D5, D6\}$ $kill(B2) = \{D1, D3\}$
 $gen(B3) = \{ \}$ $kill(B3) = \{ \}$



	in1	out1	in2	out2	in3	out3
B0	{}	{D1, D2}	{}	{D1, D2}	{}	{D1, D2}
B1	{}	{D3, D4}	{D1, D2}	{D3, D4}	{D1, D2}	{D3, D4}
B2	{}	{D5, D6}	{D1, D2}	{D2, D5, D6}	{D1, D2}	{D2, D5, D6}
B3	{}	{}	{D3, D4, D5, D6}	{D3, D4, D5, D6}	{D2, D3, D4, D5, D6}	{D2, D3, D4, D5, D6}

Algorithm for Reaching Definitions

for each basic block B

compute $\text{gen}(B)$ and $\text{kill}(B)$

$\text{out}(B) = \{\}$

Can you do better?
Hint: Worklist

do {

for each basic block B

$\text{in}(B) = \bigcup \text{out}(P)$ where $P \in \text{pred}(B)$

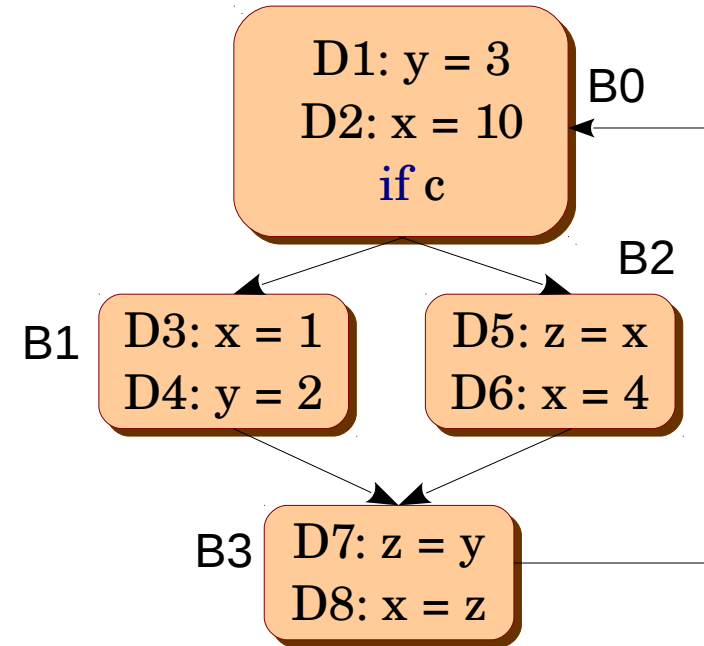
$\text{out}(B) = \text{gen}(B) \cup (\text{in}(B) - \text{kill}(B))$

} **while** $\text{in}(B)$ changes for any basic block B ₈

Classwork

- $in(B) = U \text{ out}(P)$ where P is a predecessor of B
- $out(B) = gen(B) \cup (in(B) - kill(B))$
- Initially, $out(B) = \{ \}$

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



	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	{}	{D3, D4}	{D1, D2}	{D3, D4}	{D1, D2, D7}	{D3, D4, D7}	{D1,2,7}	{D3,4,7}
B2	{}	{D5, D6}	{D1, D2}	{D1, D5, D6}	{D1, D2, D7}	{D1, D5, D6}	{D1,2,7}	{D1,5,6}
B3	{}	{D7, D8}	{D3, D4, D5, D6}	{D4, D7, D8}	{D1, D3, D4, D5, D6}	{D1, D4, D7, D8}	{D1,3,4,5,6,7}	{D1,4,7,8}

DFA for Reaching Definitions

Domain	Sets of definitions
Transfer function	$\text{in}(B) = \cup \text{out}(P)$ $\text{out}(B) = \text{gen}(B) \cup (\text{in}(B) - \text{kill}(B))$
Direction	Forward
Meet / confluence operator	\cup
Initialization	$\text{out}(B) = \{ \}$

DFA for Live Variables

Domain	Sets of variables
Transfer function	$\text{in}(B) = \text{use}(B) \cup (\text{out}(B) - \text{def}(B))$ $\text{out}(B) = \bigcup \text{in}(S)$ where S is a successor of B
Direction	Backward
Meet / confluence operator	\cup
Initialization	$\text{in}(B) = \{ \}$

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**.

Classwork

- Write an algorithm for Live Variable Analysis

```
for each basic block B
  compute gen(B) and kill(B)
  out(B) = {}
do {
  for each basic block B
    in(B) =  $\bigcup$  out(P) where P  $\in$  pred(B)
    out(B) = gen(B)  $\cup$  (in(B) - kill(B))
  } while in(B) changes for any basic block B
```

Algo for
reaching
definitions

Domain	Sets of variables
Transfer function	$in(B) = use(B) \cup (out(B) - def(B))$ $out(B) = \bigcup in(S)$ where S is a successor of B
Direction	Backward
Meet / confluence operator	\cup
Initialization	$in(B) = \{ \}$

Parameters
for live
variable
analysis

Direction and Confluence

	Forward	Backward
U	Reaching Definitions	Live Variables
n	Common Subexpressions	Very Busy Expressions

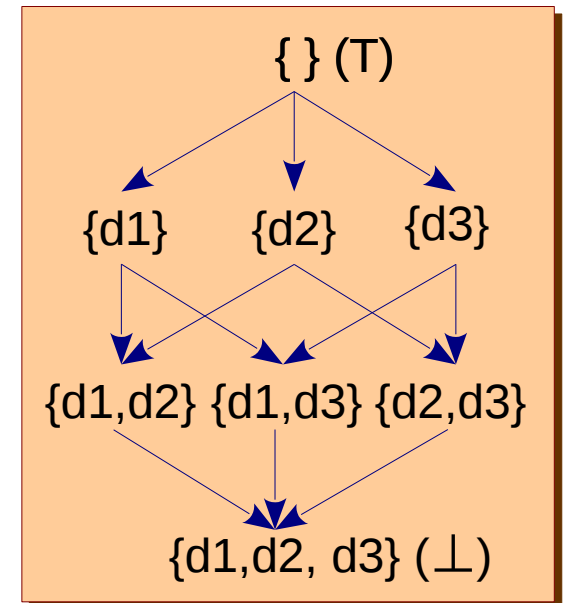
Data Flow Framework

- 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 $f_k(f_{k-1}(\dots f_2(f_1(f_0(T))\dots))$
- $MOP(x) = \sqcap f_Q(T)$

*Meet over all paths
Path enumeration is expensive*

Structure in Data Flow Framework

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



Reaching Definitions Lattice

Monotone Framework

- A framework $\langle \mathcal{L}, \Pi, \mathcal{F} \rangle$ is monotone if \mathcal{F} is monotonic, i.e.,

$$(\forall f \in \mathcal{F})(\forall x, y \in \mathcal{L}), x \geq y \Rightarrow f(x) \geq f(y)$$

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

Distributive Framework

- A framework $\langle \mathcal{L}, \sqcap, \mathcal{F} \rangle$ is distributive if \mathcal{F} is distributive, i.e.,
$$(\forall f \in \mathcal{F})(\forall \mathbf{x}, \mathbf{y} \in \mathcal{L}) f(\mathbf{x} \sqcap \mathbf{y}) \leq f(\mathbf{x}) \sqcap f(\mathbf{y})$$
- 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, $\text{MFP} \leq \text{MOP} \leq \text{Perfect solution}$.
- **If distributive, $\text{MFP} = \text{MOP}$.**
- Every distributive function is also monotonic.

Outline

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

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?

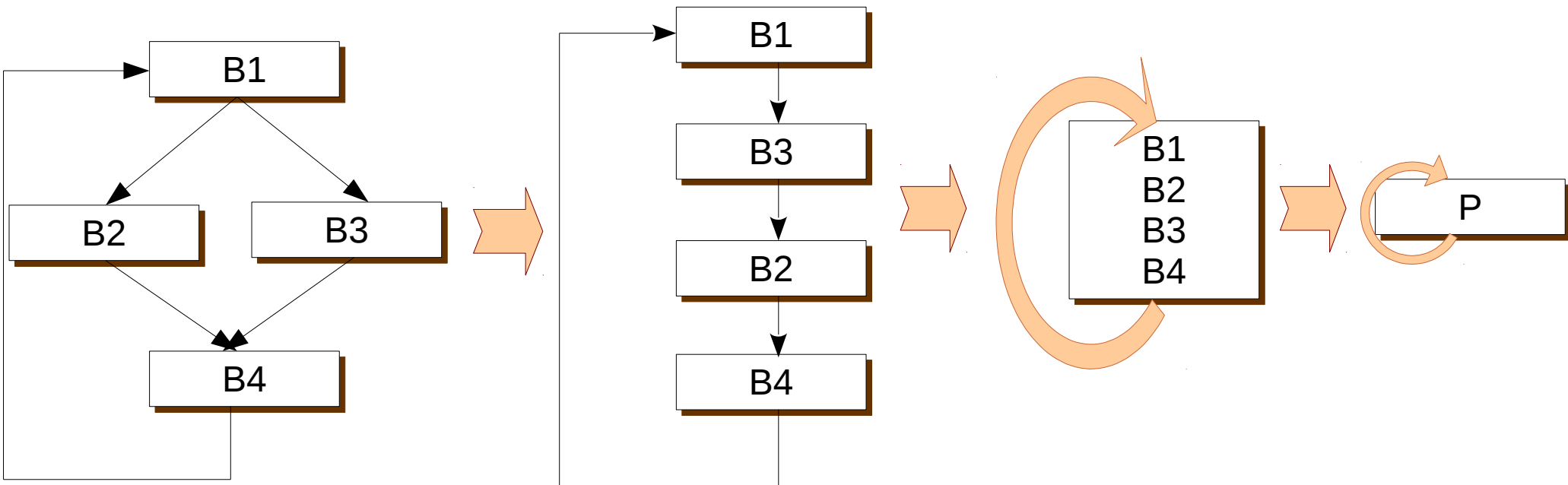
Flow-sensitivity

L0: a = 0;
L1: a = 1;
L2: ...

Flow-sensitive solution: *at L1 a is 0, at L2 a is 1*

Flow-insensitive solution: *in the program a is in {0, 1}*

Flow-insensitive analyses ignore the control-flow in the program.

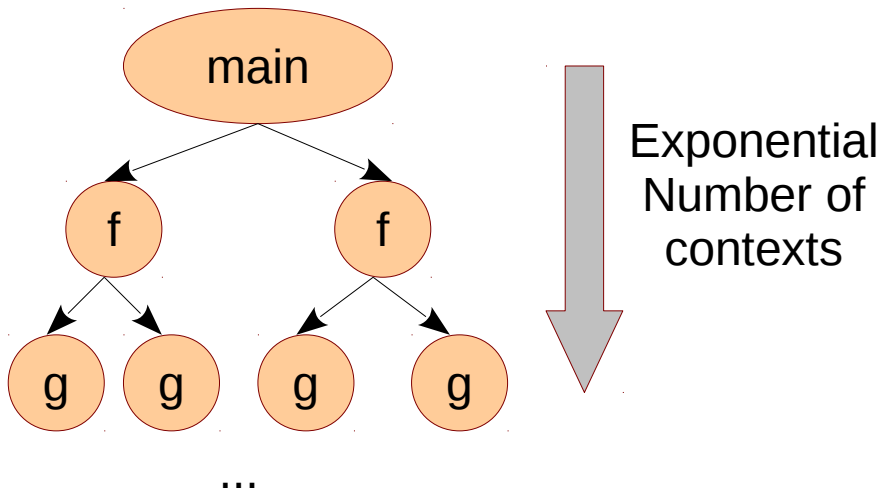


Context-sensitivity

```
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

Context-insensitive solution:
y is in {0, 1} in the program



Along main-f1-g1, ...
Along main-f1-g2, ...
Along main-f2-g1, ...
Along main-f2-g2, ...

Exponential time requirement

Exponential storage requirement

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

Context-insensitive solution:
Inter-procedural —→ *y is in {0, 1} in the program*
intra-procedural —→ *y is in $\{-\infty, +\infty\}$ in the program*

Path-sensitivity

```
if (a == 0)
    b = 1;
else
    b = 2;
```

Path-sensitive solution:

b is 1 when a is 0, b is 2 when a is not 0

Path-insensitive solution:

b is in {1, 2} in the program

```
if (c1)
    while (c2) {
        if (c3)
            ...
        else
            for (; c4; )
                ...
    }
else
    ...
```

```
c1 and c2 and c3, ...
c1 and c2 and !c3 and c4, ...
c1 and c2 and !c3 and !c4, ...
c1 and !c2, ...
!c1 ...
...
```

Field-sensitivity

```
struct T s;
```

```
s.a = 0;
```

```
s.b = 1;
```

Field-sensitive solution:

s.a is 0, s.b is 1

Field-insensitive solution:

s is in {0, 1}

Aggregates are collapsed into a single variable.
e.g., arrays, structures, unions.

This reduces the number of variables tracked during the analysis and reduces precision.

A Note on Abstraction

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

```
?  
x = 0;  
T  
++x;  
F  
--x;  
?
```

A Note on Choosing Abstraction

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

```
?  
x = 0;  
T  
++x;  
F  
--x;  
?
```

Maintain two bits for value of x
Initialized to **00**

```
??  
x = 0;  
00  
++x;  
01  
--x;  
00
```

Maintain one bit for $x == 0$
Another bit for $x < 2$
Initialized to **00**

```
??  
x = 0;  
11  
++x;  
01  
--x;  
11
```

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

Abstraction Storage

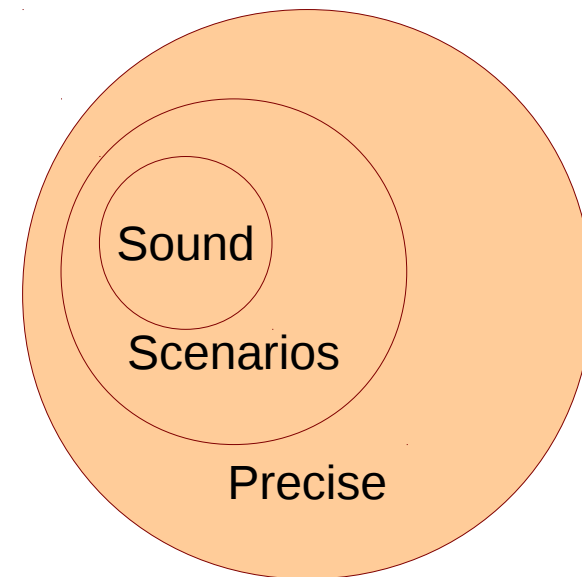
- Saturating counters
- Number of values stored faithfully with $\log(n)$ bits – $(n-2)$
- Additional information may help increase the range, e.g., type information as unsigned.

Conservative Analysis

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

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 precise if it does not disable optimization for any possible scenario.



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.

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 $p \rightarrow \{x\}$, O1 is enabled and O2 is suppressed.
 - Thus, conservative for one is precise for another.
 - And sound for one is unsound for another.

Optimization-specific Soundness

- Consider O1 that converts multiplication by 2 to a left-bit-shift operation ($x * 2$ to $x \ll 1$).
- Consider O2 that has uses a special circuit (fast operation) when there is a sum of reciprocals of powers of 2 ($1 + \frac{1}{2} + \frac{1}{4} + \dots$)
- 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.

Acknowledgements

Course notes from

- Katheryn McKinley
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