# Mechanics of Static Analysis 

## David Schmidt

Kansas State University

www.cis.ksu.edu/~schmidt

## Outline

1. Small-step semantics: trace generation
2. State generation and collecting semantics
3. Data-flow analysis
4. Ensuring termination
5. Typing rules and big-step semantics
6. Interprocedural analysis

## Static analysis

A static analysis of a program is a sound, finite, and approximate calculation of the program's execution semantics.

Approximate: not exact - computes properties or aspects of the execution semantics, such as pre- or post-conditions, invariants, data types, patterns of trace, or ranges-of-values.

Sound: consistent with the concrete, execution semantics - a sound overapproximation describes a superset of the program's executions (safe descriptions); a sound underapproximation describes a subset of the program's executions (live descriptions). We will focus on overapproximations.

Finite: regardless of the program and its approximate semantics, the analysis terminates.

## The most basic static analysis is trace generation

```
po: while (x != 1) {
    p
        p}\mp@subsup{2}{}{:}\mathrm{ then }\textrm{x}=\mathbf{x}\operatorname{div2;
        p3: else x = 3*x + 1;
        }
p4: exit
```

                            Note: \(p_{i}, v\) abbreviates \(p_{i},\langle x: v\rangle\)
    Abstract overapproximating trace:
        po, even \(\leftarrow\)
    \(p_{4}\), od
    

Two concrete traces:


The abstract tree (abstract model) is a static analysis of those concrete executions that use an even-valued input.

Each concrete transition, $p_{\mathfrak{i}}, s \rightarrow p_{\mathfrak{j}}, f_{\mathfrak{i}}(s)$, is reproduced by a corresponding abstract transition, $p_{i}, a \rightarrow p_{j}, f_{i}^{\#}(a)$, where $s \in \gamma(a)$. $\left(f_{i}^{\#}=\alpha \circ f_{i} \circ \gamma\right.$.)

The traces embedded in the abstract trace tree simulate all the concrete traces, e.g., this concrete trace,

$$
p_{0}, 4 \rightarrow p_{1}, 4 \rightarrow p_{2}, 4 \rightarrow p_{0}, 2 \rightarrow p_{1}, 2 \rightarrow p_{2}, 2 \rightarrow p_{0}, 1 \rightarrow p_{4}, 1
$$

is simulated by this abstract trace, which is extracted from the abstract computation tree:
$p_{0}$, even $\rightarrow p_{1}$, even $\rightarrow p_{2}$, even $\rightarrow p_{0}$, even $\rightarrow p_{1}$, even $\rightarrow p_{2}$, even $\rightarrow$ $p_{0}$, odd $\rightarrow p_{4}$, odd
because we used a Galois connection to justify the soundness of the transition steps in the abstract trace tree.

In this fashion, a static analysis can generate an abstract test or abstract model, which covers a range of concrete inputs.

## State reachability and collecting semantics

If we are interested only in the reachable states and not their orderings in the trace, we compute the program's collecting semantics as a nondecreasing sequence of sets of program states. The collecting semantics is an abstraction of trace-generation semantics.

## Collecting semantics, concrete and abstract:

$$
\begin{aligned}
& \left\{p_{0}, 4\right\} \\
& \left\{p_{0}, 4 ; p_{1}, 4\right\} \\
& \left\{p_{0}, 4 ; p_{1}, 4 ; p_{2}, 4\right\} \\
& \left\{p_{0}, 4 ; p_{1}, 4 ; p_{2}, 4 ; p_{0}, 2\right\} \\
& \quad \ldots \\
& \left\{p_{0}, 4 ; p_{1}, 4 ; p_{2}, 4 ; p_{0}, 2 ;\right. \\
& \left.\quad p_{1}, 2 ; p_{2}, 2 ; p_{0}, 1 ; p_{4}, 1\right\}
\end{aligned}
$$

$$
\left\{p_{0}, \text { even }\right\}
$$

$$
\left\{p_{0}, \text { even } ; p_{4}, \text { even } ; p_{1}, \text { even }\right\}
$$

$$
\left\{p_{0}, \text { even } ; p_{4}, \text { even } ; p_{1}, \text { even } ; p_{2}, \text { even }\right\}
$$

$$
\left\{\mathfrak{p}_{0}, \text { even } ; p_{4}, \text { even; } p_{1}, \text { even; } p_{2}, \text { even } ;\right.
$$

$$
\left.p_{0}, a n y\right\}
$$

## "Sticky" collecting semantics

A semantics of form, $\wp($ ProgramPoint $\times$ AbsStore), is "attaching" AbsStore values to each program point - the isomorphic representation, ProgramPoint $\rightarrow \wp($ (AbsStore), is called the (relational) "sticky" collecting semantics:

$$
\begin{aligned}
& {\left[p_{0} \mapsto\{\text { even, any }\} ; p_{1} \mapsto\{\text { even, any }\} ; p_{2} \mapsto\{\text { even }\} ;\right.} \\
&\left.p_{3} \mapsto\{\text { odd }\} ; p_{4} \mapsto\{\text { even, any }\}\right]
\end{aligned}
$$

The above can be abstracted to a function in ProgramPoint $\rightarrow$ AbsStore, the independent-attribute semantics:

$$
\left[p_{0} \mapsto a n y ; p_{1} \mapsto \text { any; } p_{2} \mapsto \text { even } ; p_{3} \mapsto \text { odd } ; p_{4} \mapsto a n y\right]
$$

which is based on this abstraction mapping:

$$
\begin{aligned}
& \alpha: \wp(\text { AbsStore }) \rightarrow \text { AbsStore } \\
& \quad \alpha(S)=\left\langle i: \bigsqcup_{s \in S} s(i)\right\rangle_{i \in \text { Identifier }}
\end{aligned}
$$

Notice that the independent-attribute semantics is less precise than its relational ancestor; for example, variables x and y might have these values at program point $p_{i}$ :

$$
\left[\ldots p_{i} \mapsto\{\langle x: \text { even, } y: \text { even }\rangle,\langle x: \text { odd, } y: o d d\rangle\} \ldots\right]
$$

meaning that $\mathrm{x}+\mathrm{y}$ computes to even at $\mathrm{p}_{\mathrm{i}}$.
But the independent-attribute abstraction,

$$
\left[\ldots p_{i} \mapsto\langle x: a n y, y: a n y\rangle \ldots\right]
$$

makes $\mathrm{x}+\mathrm{y}$ compute to any, losing precision.
Note also that we could define a collecting version of a trace-generation semantics, which generates an analysis of form ProgramPoint $\rightarrow \wp$ (Trace).

## Formalizing the "small steps": transfer functions

A trace's transitions, $\mathrm{pp}_{\mathrm{i}}, s \longrightarrow \mathrm{pp}_{\mathrm{i}}, \mathrm{s}^{\prime}$, are computed with a control-flow graph annotated with transfer functions.

```
po: y = 1;
p
        p
        p3:x = x div2;
        }
p4: exit
```



Concrete transfer functions: $\langle u, v\rangle$ abbreviates $\langle x: u, y: v\rangle$

$$
\begin{aligned}
& \mathrm{f}_{0}\langle\mathrm{u}, v\rangle=\langle\mathrm{u}, 1\rangle \\
& \mathrm{f}_{1 \mathrm{t}}(\mathrm{~s})=\left\{\begin{array}{ll}
\mathrm{s} & \text { if } s=\langle 2 \mathrm{u}, v\rangle \\
\perp & \text { otherwise }
\end{array} \quad \mathrm{f}_{1 \mathrm{f}}(\mathrm{~s})= \begin{cases}\mathrm{s} & \text { if } s=\langle 2 \mathrm{u}+1, v\rangle \\
\perp & \text { otherwise }\end{cases} \right. \\
& \mathrm{f}_{2}\langle\mathrm{u}, v\rangle=\langle\mathrm{u}, v * \mathrm{u}\rangle \\
& \mathrm{f}_{3}\langle\mathrm{u}, v\rangle=\langle\mathrm{u} / 2, v\rangle
\end{aligned}
$$

Important: configurations of form, $p_{i}, \perp$, cannot appear in a trace.

The abstract transfer functions are derived as $f^{\#}=\alpha \circ f \circ \gamma$

```
\(p_{0}: ~ y=1 ;\)
\(p_{1}\) : while Even (x) \{
        \(p_{2}: y=y * x\);
        \(p_{3}: x=x \operatorname{div} ;\)
        \}
\(p_{4}\) : exit
```



As usual, $\langle u, v\rangle$ abbreviates $\langle x: u, y: v\rangle$
Note: all $\mathrm{f}^{\#}$ are totally strict: $\mathrm{f}^{\#}\langle u, \perp\rangle=\mathrm{f}^{\#}\langle\perp, v\rangle=\langle\perp, \perp\rangle$
$f_{0}^{\#}\langle u, v\rangle=\langle u, o d d\rangle$
$\mathrm{f}_{1 \mathrm{t}}^{\#} \mathrm{~s}=\mathrm{s} \sqcap\langle$ even, $T\rangle$

$$
\mathrm{f}_{1 f}^{\#} \mathrm{~s}=\mathrm{s} \sqcap\langle\mathrm{odd}, \mathrm{~T}\rangle
$$

$f_{2}^{\#}\langle u, v\rangle=\langle\mathfrak{u}, w\rangle$, where $w= \begin{cases}\text { even } & \text { if } \mathfrak{u}=\text { even or } v=\text { even, else } \\ \text { odd } & \text { if } \mathfrak{u}=\text { odd and } v=\text { odd, else } \\ \top & \end{cases}$
$f_{3}^{\#}\langle u, v\rangle=\langle T, v\rangle$
Note: $\langle\mathrm{a}, \mathrm{b}\rangle \sqcap\left\langle\mathrm{a}^{\prime}, \mathrm{b}^{\prime}\right\rangle=\left\langle\mathrm{a} \sqcap \mathrm{a}^{\prime}, \mathrm{b} \sqcap \mathrm{b}^{\prime}\right\rangle$.

## Flow equations calculate the (sticky, collecting) independent-attribute semantics

The value "attached" to program point $p_{i}$ is defined by the equational pattern,

$$
p_{i} \text { Store }=\bigsqcup_{p_{j} \in \operatorname{pred}\left(\mathfrak{p}_{i}\right)} f_{j}^{\#}\left(p_{j} \text { Store }\right)
$$

The collecting semantics of $p_{i}$ is the join of the answers computed by $p_{i}$ 's predecessor transfer functions.

Flow equations for previous example:

$$
\begin{aligned}
& p_{0} \text { Store }=\langle x: \top, y: T\rangle \\
& p_{1} \text { Store }=f_{0}^{\#}\left(p_{0} \text { Store }\right) \sqcup f_{3}^{\#}\left(p_{3} \text { Store }\right) \\
& p_{2} \text { Store }=f_{11}^{\#}\left(p_{1} \text { Store }\right) \\
& p_{3} \text { Store }=f_{2}^{\#}\left(p_{2} \text { Store }\right) \\
& p_{4} \text { Store }=f_{1 f}^{\#}\left(p_{1} \text { Store }\right)
\end{aligned}
$$

We solve the flow equations by calculating approximate solutions in stages until the least fixed point is reached.

Note: $u, v$ abbreviates $\langle x: u, y: v\rangle$.

| stage | $p_{0}$ Store | $p_{1}$ Store | $p_{2}$ Store | $p_{3}$ Store | $p_{4}$ Store |
| :--- | :--- | :--- | :--- | :--- | :--- |
| 0 | $\perp, \perp$ | $\perp, \perp$ | $\perp, \perp$ | $\perp, \perp$ | $\perp, \perp$ |
| 1 | $T, T$ | $\perp, \perp$ | $\perp, \perp$ | $\perp, \perp$ | $\perp, \perp$ |
| 2 | $T, T$ | T, odd | $\perp, \perp$ | $\perp, \perp$ | $\perp, \perp$ |
| 3 | T, $T$ | T, odd | even, odd | $\perp, \perp$ | odd, odd |
| 4 | $T, T$ | T, odd | even, odd | even, even | odd, odd |
| $\cdots$ |  |  |  |  |  |
| 8 | T, $T$ | T, $T$ | even, $T$ | even, even | odd, $T$ |
| 9 | T, $T$ | T, $T$ | even, $T$ | even, even | odd, $T$ |

A faster algorithm uses a worklist that remembers exactly which equations should be recalculated at each stage.

To summarize, we annotate the control-flow graph with the non- $\perp$ values that arrive at the program points:

$$
\begin{aligned}
& \quad \mathrm{T}, \top \\
& p_{0}: \quad \mathbf{y}=1 ; \\
& \downarrow \\
& \quad \top, \text { odd } \bigsqcup \top, \text { even }=\top, \top
\end{aligned}
$$

$p_{1}$ : while Even (x)


The analysis approximates the stores that arrive at the program points.

The equational format is called data-flow analysis. It is the most popular static analysis format.

## Variants of data-flow analysis

We might vary whether the "data flow" goes forwards or backwards; we might also vary whether information is "joined" ( $\sqcup$ ) or "met" ( $\square$ ):

## Forwards-possibly:

$$
p_{i} \text { Store }=\sqcup_{\mathfrak{p}_{\mathfrak{j}} \in \operatorname{pred}\left(\mathfrak{p}_{\mathfrak{i}}\right)} f_{\mathfrak{j}}\left(p_{j} \text { Store }\right)
$$

## Forwards-necessarily:

$$
p_{i} \text { Store }=\sqcap_{\mathfrak{p}_{\mathfrak{j}} \in \operatorname{pred}\left(\mathfrak{p}_{\mathfrak{i}}\right)} f_{\mathfrak{j}}\left(p_{\mathfrak{j}} \text { Store }\right)
$$

## Backwards-possibly:

$$
p_{i} \text { Store }=f_{i}^{-1}\left(\cup_{p_{j} \in \operatorname{succ}\left(\mathfrak{p}_{i}\right)} p_{j} \text { Store }\right)
$$

## Backwards-necessarily:

$$
p_{i} \text { Store }=f_{i}^{-1}\left(\cap_{p_{j} \in \operatorname{succ}\left(\mathfrak{p}_{i}\right)} p_{j} \text { Store }\right)
$$

The backwards analyses almost always compute sets of values, hence the use of $\cup$ and $\cap$.

A forwards analysis computes "histories" that arrive at a point:

## forwards analysis $\boldsymbol{=}$ postcondition semantics

$p_{i}$ Store $=a$ approximates the set of traces of the form
$p_{0}, s_{0} \rightarrow p_{1}, s_{1} \rightarrow \cdots \rightarrow p_{i}, s_{i}\left(\right.$ where $\left.s_{i} \in \gamma(a)\right)$
A backwards analysis computes the "futures" from a program point:

## backwards analysis = precondition semantics

$p_{i}$ Store $=a$ approximates the set of traces of the form
$p_{i}, s_{i} \rightarrow \cdots \rightarrow p_{\text {exit }}, s_{\text {final }}$ (where $s_{i} \in \gamma(a)$ )
A possibly analysis predicts a "superset" of the actual computations: if $p_{i}$ Store $=a$, then for all concrete values, $c \sqsubseteq c \gamma(a)$, that arrive at $p_{i}$, we have $c \sqsubseteq c \gamma(a)$ - all possibilities are predicted.

A necessarily analysis predicts a "subset" of the actual computations: if $p_{i}$ Store $=a$, then there exists some $c \sqsubseteq c \gamma(a)$, that arrives at $p_{i}$.

The data-flow example developed earlier in this Lecture computed answers of the form,

$$
p_{i} \text { Store }=a
$$

which asserted, if store $s$ arrives at program point $p_{i}$, then $s \in \gamma(a)$.
But there are data-flow analyses where $p_{i}$ Store $=$ a means that all execution traces that arrive at $p_{i}$ contain some pattern of program points and stores, described by a.

We will develop the Galois-connection formalities in the next Lecture, but just now we study two examples, used by compilers for improving register allocation in target code. These examples compute sets of program phrases that describe patterns within execution traces.

The examples show variations of the forwards/backwards and possibly/necessarily forms of data-flow analysis.

## Forwards-necessarily-reaching definitions: which assignments must reach their successors

inReachp $_{i}=\bigcap_{p_{j} \in \operatorname{pred}\left(p_{i}\right)}$ outReachp ${ }_{j}$
outReachp $_{i}=f_{i}^{\#}\left(\right.$ inReachp $\left._{i}\right)=\left(\right.$ inReachp $\left._{i}-\operatorname{kill}_{i}\right) \cup \operatorname{gen}_{i}$
(the transfer function computes a set of assignment statements)
for $p_{i}: x=e,\left\{\begin{array}{l}\operatorname{kill}_{i}=\left\{p_{j} \mid p_{j}: x=\ldots\right\} \\ \operatorname{gen}_{i}=\left\{p_{i}\right\}\end{array} \quad\right.$ for $p_{i}:$ if $e,\left\{\begin{array}{l}\operatorname{kill}_{i}=\{ \} \\ \operatorname{gen}_{i}=\{ \}\end{array}\right.$

Sample analysis:

$$
\begin{aligned}
p_{0}: & x=0 \\
& \downarrow\left\{p_{0}\right\}
\end{aligned}
$$

## Explanation:

If $p^{\prime} \in$ inReachp $p_{i}$, where $p^{\prime}$ labels the assignment, $p^{\prime}: v=e$, then all traces from $p_{0}$ to $p_{i}$ must possess the pattern,

$$
p_{0} \rightarrow \cdots \rightarrow p^{\prime} \rightarrow \cdots \rightarrow p_{i}
$$

and no assignment, $\mathrm{v}=\mathrm{e}^{\prime}$, occurs between $\mathrm{p}^{\prime}$ and $\mathrm{p}_{\mathrm{i}}$ in the trace. If $p^{\prime} \in$ in Reachp $p_{i}$ holds, then the assignment at $p^{\prime}$ should save its right-hand-side value in a register for quick access by $p_{i}$.

## Backwards-possibly-live variables: which variables might be referenced in the future

$$
\begin{aligned}
& \text { outLivep }_{i}=\bigcup_{p_{j} \in \operatorname{succ}\left(p_{i}\right)} \text { inLivep }_{j} \\
& \text { inLivep }_{i}=f_{i}^{\#}\left(\text { outLivep }_{i}\right)=\left(\text { outLivep }_{i}-\text { kill }_{i}\right) \cup \text { gen }_{i}
\end{aligned}
$$

(the transfer function computes a set of variable names)

$$
\begin{aligned}
& \text { for } p_{i}: x=\mathrm{e}\left\{\begin{array} { l l } 
{ \operatorname { k i l l } _ { i } = \{ x \} } \\
{ \operatorname { g e n } _ { i } = \{ v | v \text { in e } \} }
\end{array} \quad \text { for } \begin{array} { l } 
{ \text { printed } } \\
{ p _ { i } : \text { while e } }
\end{array} \left\{\begin{array}{l}
\operatorname{kill}_{i}=\{ \} \\
\operatorname{gen}_{i}=\{v \mid v \text { in e }\}
\end{array}\right.\right. \\
& \{\mathrm{x}\}=\text { inLine } p 0 \\
& p_{0}: \underset{y}{y}=1 ; \\
& \{\mathrm{x}, \mathrm{y}\}=\text { outLive } p 0=\text { inLine } p 1
\end{aligned}
$$

## $p_{1}:$ while Even $(x)<\ldots$

Sample analysis:

$p_{4}:$ print $y \quad p_{2}: y=2 * x ;$ \{ \}

$$
\begin{gathered}
\hat{\{ }\{\mathbf{x}, \mathbf{y}\} \\
p_{3}: \mathbf{x}=\mathbf{x} \operatorname{div} \mathbf{z}
\end{gathered}\{\mathbf{x}, \mathbf{y}\}
$$

## Explanation:

If there is a concrete execution trace containing the pattern,

$$
p_{i} \rightarrow \cdots \rightarrow p^{\prime} \rightarrow \cdots \rightarrow p_{\text {exit }}
$$

such that $p^{\prime}$ references variable v and no assignment to v appears between $p_{i}$ and $p^{\prime}$, then $v \in$ out Livep $_{i}$.

If $v \notin$ outLivep $_{i}$ holds, then v’s value should be removed from all registers upon completion of $p_{i}$ 's execution - v is a "dead variable" after $p_{i}$.

## Termination: Constant propagation reviewed

$$
\begin{aligned}
& p_{0}: \mathrm{x}=1 ; \mathrm{y}=2 ; \\
& p_{1}: \text { while }(\mathrm{x}<\mathrm{y}+\mathrm{z}) \\
& \quad p_{2}: \mathrm{x}=\mathrm{x}+1 ; \\
& p_{3}: \text { exit }
\end{aligned}
$$


where $m+n$ is interpreted

$$
\begin{aligned}
& k_{1}+\mathrm{k}_{2} \longrightarrow \operatorname{sum}\left(k_{1}, k_{2}\right), \\
& \quad T \neq k_{i} \neq \perp, i \in 1 . .2 \\
& \top+k \longrightarrow \top \\
& k+\top \longrightarrow T
\end{aligned}
$$

The naive trace does not terminate.

Abstract trace: $p_{0},\langle T, T, T\rangle$ $p_{1},\langle 1,2, T\rangle$ $\downarrow>p_{3},\langle 1,2, T\rangle$
$p_{2},\langle 1,2, \top\rangle$
$p_{1},\langle 2,2, T\rangle$

$$
\downarrow \nabla_{p_{3},\langle 2,2, T\rangle}
$$

$p_{2},\langle 2,2, T\rangle$
$p_{1},\langle 3,2, \top\rangle$

## Finite-height and $\sqcup$ give termination

|  | stage | poStore | $p_{1}$ Store | $\mathrm{p}_{2}$ Store | $\mathrm{p}_{3}$ Store |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 | T, T, T | $\perp, \perp, \perp$ | $\perp, \perp, \perp$ | $\perp, \perp, \perp$ |
|  | 2 | $\top, \top, \top$ | 1,2, $\top$ | $\perp, \perp, \perp$ | $\perp, \perp, \perp$ |
|  | 3 | ', T, T | 1,2, T | 1,2, $\top$ | 1,2, $\top$ |
|  | 4 | $\top, \top, \top$ | T, 2, T | 1,2, $\top$ | 1,2, $\top$ |
|  | 5 | $\top, \top, \top$ | $\top, 2, \top$ | T, 2, T | T, 2, T |
|  | 6 | $\top, \top, \top$ | $\top, 2, \top$ | $\top, 2, \top$ | T, 2, T |

Termination is guaranteed because the transfer functions and $\bigsqcup$ are monotonic (each stage has values not smaller than its predecessors) and the abstract domain, Const, has finite height - there are no infinitely ascending sequences (the stages cannot increase forever). (Indeed, the longest seqence in Const goes: $\perp \sqsubseteq \mathrm{k} \sqsubseteq T$.)

## Termination: Array-bounds checking reviewed

Integer variables receive values from the interval domain,

$$
I=\{[i, j] \mid i, j \in \operatorname{Int} \cup\{-\infty,+\infty\}\} .
$$

We define $[a, b] \sqcup\left[a^{\prime}, b^{\prime}\right]=\left[\min \left(a, a^{\prime}\right), \max \left(b, b^{\prime}\right)\right]$.

$$
\begin{aligned}
& \begin{array}{l}
\text { int } a=\text { new int }[10] ; \ldots-.--i=[0,0] \\
i=0 ;
\end{array}
\end{aligned}
$$

$$
\begin{aligned}
& -i=[0,0] \square[1,1] \sqcap[-\infty, 9]=[0,1] \\
& i=i+\frac{1 ;}{\underset{\gtrless}{n} \ldots p_{1}-i=[1,1]} \\
& -i=[1,1] \bigsqcup[2,2]=[1,2]
\end{aligned}
$$

This example terminates: i's ranges are
at $p_{1}:[0 . .9]$
at $p_{2}:[1 . .10]$
at loop exit : [1..10] $\sqcap[10,+\infty]=[10,10]$

But others might not, because the domain is not finite height:

$$
\begin{aligned}
& i=0 ;<\ldots-\cdots i=[0,0]
\end{aligned}
$$

$$
\begin{aligned}
& \text { \} } \\
& \leqslant \ldots-\cdots \quad \mathrm{i}=[] \quad \text { (dead code) }
\end{aligned}
$$

The analysis generates the infinite sequence of stages, $[0,0],[0,1], \ldots,[0, i], \ldots$ as i's value in the loop's body.

The domain of intervals, where $[\mathrm{i}, \mathrm{j}] \sqsubseteq\left[\mathrm{i}^{\prime}, \mathrm{j}^{\prime}\right]$ iff $\mathrm{i} \leq \mathrm{j}$ and $\mathrm{j} \leq \mathrm{j}^{\prime}$, has infinitely ascending chains.

To forcefully terminate the analysis, we can replace the $\sqcup$ operation by $\nabla$, called a widening operator.

$$
[] \nabla[i, j]=[i, j] \quad[i, j] \nabla\left[i^{\prime}, j^{\prime}\right]=\begin{aligned}
& {\left[\text { if } i^{\prime}<i \text { then }-\infty \text { else } i,\right.} \\
& \text { if } \left.j^{\prime}>j \text { then }+\infty \text { else } j\right]
\end{aligned}
$$

The widening operator, which guarantees finite convergence for all increasing sequences on the interval domain, quickly terminates the example:

$$
\begin{aligned}
& i=0 ;<\cdots-\quad i=[0,0] \\
& \text { while true }\{ \\
& i=i+\underset{1 ;}{=}--i=[0,0] \nabla[1,1]=[0,+\infty] \\
& \text { \} } \\
& \leqslant \cdots-\cdots-\cdots \quad \text { (dead code) }
\end{aligned}
$$

but in general, it can lose much precision:

```
int a = new int[10];
i = 0; <<-----i=[0,0]
while (i < 10) {
            ... a[i]<<-- - i=[0,0]\nabla[1,1]=[0,+\infty]
            i = i + 1;
}
    <<\cdots------i=[10,+\infty]
```

For this reason, a complementary operation, $\triangle$, called a narrowing operation, can be used after $\nabla$ gives convergence to recover some precision and retain a fixed-point solution.

We will not develop $\triangle$ here, but for the interval domain, a suitable $\triangle$ tries to reduce $-\infty$ and $+\infty$ to finite values. For the last example, the convergent value, $[0,+\infty]$, in the loop body would be narrowed to $[0,10]$, making i's value on loop exit $[10,10]$.

Another approach is to use multiple "thresholds" for widening, e.g. $-\infty,\left(2^{-31}-1\right), 0$, etc. for lower limits, and $\left(2^{31}-1\right)$ and $+\infty$ for upper limits.

## Structured（big－step）static analysis

Given a block of statements，B，we might wish to calculate the values that＂enter＂and＂exit＂from B．If B is coded in a structured language， we can define the static analysis to compute a structured transfer function for B：

$$
C::=p: x=E\left|C_{1} ; C_{2}\right| \text { if } E C_{1} C_{2} \mid \text { while } E C
$$

A sample structured analysis that ignores tests：$\llbracket C \rrbracket: A_{\text {in }} \rightarrow A_{\text {out }}$

$$
\begin{aligned}
& \llbracket p: x=E \rrbracket i n=f_{p}^{\#}(i n) \quad \text { (the transfer function for } p \text { ) } \\
& \llbracket \mathrm{C}_{1} ; \mathrm{C}_{2} \rrbracket \mathrm{in}=\llbracket \mathrm{C}_{2} \rrbracket\left(\llbracket \mathrm{C}_{1} \rrbracket \mathrm{in}\right) \\
& \llbracket \text { if } E C_{1} \mathrm{C}_{2} \rrbracket \mathrm{in}=\llbracket \mathrm{C}_{1} \rrbracket \text { in } \sqcup \llbracket \mathrm{C}_{2} \rrbracket \text { in } \\
& \text { 【while E C】in }=\text { in } \sqcup \text { out }_{C} \text {, } \\
& \text { where out }{ }_{C}=\bigsqcup_{i \geq 0} \text { out }_{i} \text {, } \\
& \text { and out }{ }_{0}=\perp_{\mathrm{A}} \text { and out } \mathrm{t}_{\mathrm{i}+1}=\llbracket \mathrm{C} \rrbracket\left(\text { in } \sqcup \mathrm{out}_{\mathrm{i}}\right)
\end{aligned}
$$

We can annotate a syntax tree with the in-and out-data - here is a forwards-possibly reaching definitions analysis, which computes sets of assignments that might reach future program points:


The analysis calculates a "local" least-fixed point at each while-loop, in contrast to a data-flow analysis, which calculates a single "global" least-fixed point for the entire program. (It is straightforward to prove that both techniques compute the same answer.)

The structured, equational style is based on denotational semantics.
The structured analysis is no more precise than the iterative, data-flow analysis (that is, a sticky, collecting semantics); indeed, $\llbracket C \rrbracket: A_{\text {in }} \rightarrow A_{\text {out }}$ is an abstraction of the data-flow analysis of $C$ in the sense that $\llbracket \mathrm{C} \rrbracket$ "forgets" the flow information of C's subphrases and returns only C's output.

## Structured analysis in inference-rule format

The style of the previous example suggests that a structured analysis pairs each phrase, $C$, with its input and outputs, $i n_{c}$ and out $t_{c}$.

We might write relational "assertions" in the formats

$$
\text { in }_{c} \mathrm{C} \text { out }_{c} \quad \text { or } \quad C: \text { in }_{c} \rightarrow \text { out }_{c} .
$$

The first format is used in Hoare-logics, the second in data-typing.
The semantics equations inspire us to write these inference rules:

$$
\begin{aligned}
& \vdash p: \mathrm{x}=\mathrm{E}: \text { in } \rightarrow \mathrm{f}_{\mathfrak{p}}^{\#}(\text { in }) \quad \frac{\vdash \mathrm{C}_{1}: \text { in } \rightarrow \text { out } \quad \vdash \mathrm{C}_{2}:{\text { out } \rightarrow \text { out }^{\prime}}_{\vdash \mathrm{C}_{1} ; \mathrm{C}_{2}: \text { in } \rightarrow \text { out }^{\prime}}}{\stackrel{\vdash \mathrm{C}_{1}: \text { in } \rightarrow \text { out }_{1} \vdash \mathrm{C}_{2}: \text { in } \rightarrow \text { out }_{2}}{\vdash \text { if E C } \mathrm{C}_{1} \mathrm{C}_{2}: \text { in } \rightarrow \text { out }_{1} \sqcup \text { out }} 2} \quad \frac{\vdash \mathrm{C}: \text { in } \sqcup \text { out } \rightarrow \text { out }}{\vdash \text { while } \mathrm{C}: \text { in } \rightarrow \text { out }}
\end{aligned}
$$

We use the rules to derive a program's analysis as a "proof."

## Reaching definitions, repeated:

$$
\begin{gathered}
\text { in } p: x=E \text { in }- \text { kill }_{x} \cup\{p\} \quad \frac{{\text { in } C_{1} \text { out out } C_{2} \text { out }^{\prime}}_{\text {in } C_{1} ; C_{2} \text { out }}}{} \begin{array}{c}
{\text { in } C_{1} \text { out }_{1} \text { in } C_{2} \text { out }_{2}}_{\text {in if } E C_{1} C_{2} \text { out }_{1} \cup \text { out }_{2}}
\end{array} \frac{\text { in } \cup \text { out } C \text { out }}{\text { in while } E \text { out }}
\end{gathered}
$$

The (inverted) proof resembles the annotated syntax tree:

$$
\} \mathrm{p} 1: \mathrm{y}=1 \text {; if } \mathrm{y}>\mathrm{x} \ldots\{\mathrm{p} 1, \mathrm{p} 2, \mathrm{p} 3\}
$$

\{ \} $\mathrm{p} 1: \mathrm{y}=1$ \{ p 1$\}$

$$
\{\mathrm{p} 1\} \text { if } \mathrm{y}>\mathrm{x} \ldots\{\mathrm{p} 1, \mathrm{p} 2, \mathrm{p} 3\}
$$

$$
\{p 1\} p 2: y=x\{p 2\} \frac{\{p 1\} \text { while } y!=x \ldots\{p 1, p 3\}}{\{p 1, p 3\} p 3: y=y+1\{p 3\}}
$$

Unlike the denotational-semantics version, the while-rule does not calculate a least-fixed point: A "guess" or "inference" of an invariant assertion is made to obtain a proof of in $\cup$ outCout that is used to prove inwhile E Cout. The program analysis is done in one pass.

The example suggests that data-typing systems defined as "inference-rule sets" are one-pass, structured static analyses:

$$
\pi \vdash x: \pi(x) \quad \frac{\pi \oplus\left[x \mapsto \tau_{1}\right] \vdash \mathrm{E}: \tau_{2}}{\pi \vdash \lambda x . \mathrm{E}: \tau_{1} \rightarrow \tau_{2}} \quad \frac{\pi \vdash \mathrm{E}_{1}: \tau_{1} \rightarrow \tau_{2} \quad \pi \vdash \mathrm{E}_{2}: \tau_{1}}{\pi \vdash \mathrm{E}_{1} \mathrm{E}_{2}: \tau_{2}}
$$

These data-typing rules, which underlie the ML languages, analyze a program in one pass and predict the range of values (data type) that the program's phrases will produce when executed:

$$
\begin{aligned}
& \gamma(\text { bool })=\text { Bool }=\{\text { true }, \text { false }\} \\
& \gamma(\text { int })=\text { Int }=\{\ldots-1,0,1, \ldots\} \\
& \gamma\left(\tau_{1} \rightarrow \tau_{2}\right)=\left\{\mathrm{f}: \text { Val } \mid \text { for all } a \in \gamma\left(\tau_{1}\right), f(a) \in \gamma\left(\tau_{2}\right)\right\}
\end{aligned}
$$

where $\mathrm{Val}=\bigcup_{i \geq 0} \mathrm{~V}_{i}$, such that $\mathrm{V}_{0}=\{ \}$ and $\mathrm{V}_{i+1}=\operatorname{Bool} \cup \operatorname{Int} \cup\left(\mathrm{V}_{i} \rightarrow \mathrm{~V}_{i}\right)$.
A guess is needed for $\tau_{1}$ in the hypotheis of the second typing rule. A typical implementation of the rules uses first-order unification to calculate an intelligent guess.

## Big-step (natural) semantics is a multi-pass analysis

$$
\begin{align*}
& \sigma \vdash p: x=E \Downarrow f_{p}(\sigma) \\
& \frac{\sigma \vdash C_{1} \Downarrow \sigma_{1} \quad \sigma_{1} \vdash C_{2} \Downarrow \sigma_{2}}{\sigma \vdash C_{1} ; C_{2} \Downarrow \sigma_{2}} \quad \frac{f_{E t}(\sigma) \vdash C_{1} \Downarrow \sigma_{1} \quad f_{E f}(\sigma) \vdash C_{2} \Downarrow \sigma_{2}}{\sigma \vdash \text { if } E C_{1} C_{2} \Downarrow \sigma_{1} \sqcup \sigma_{2}} \\
& \frac{f_{E t}(\sigma) \vdash C \Downarrow \sigma^{\prime} \quad \sigma^{\prime} \vdash \text { while E C } \Downarrow \sigma^{\prime \prime}}{\sigma \vdash \text { while E } C \Downarrow f_{\mathrm{Ef}}(\sigma) \sqcup \sigma^{\prime \prime}}
\end{align*}
$$

Recall that $f_{p}$ is a transfer function and that $f_{E t}$ and $f_{E f}$ "fi lter" the store, e.g.,

$$
f_{x>2 t}\langle x: 4, y: 3\rangle=\langle x: 4, y: 3\rangle \text {, whereas } f_{x>2 t}\langle x: 0, y: 3\rangle=\perp .
$$

An example: if Even( $x$ ) ( $x=0$ ) (while $x \neq 3(x=x+1)$ )


An abstract big-step tree: using the same inference rules but with abstract transfer functions for Parity $=\{\perp$, even, odd, $T\}$, we generate an abstract tree that is infinite but regular:


Variable $X$ denotes the answer from the repeated loop subderivation:

$$
X=\langle\mathrm{x}: \mathrm{odd}\rangle \sqcup X
$$

The least solution sets $X=\langle\mathrm{x}:$ odd $\rangle$.

## Big-step semantics naturally supports interprocedural analysis

$$
\frac{\text { func } \mathrm{f}(\mathrm{x}) \text { local } \mathrm{y} ; \mathrm{C} . \quad[\mathrm{x} \mapsto \llbracket \mathrm{E}] \sigma][\mathrm{y} \mapsto \perp] \vdash \mathrm{C} \Downarrow \sigma^{\prime}}{\sigma \vdash \mathrm{z}=\mathrm{f}(\mathrm{E}) \Downarrow \sigma\left[\mathrm{z} \mapsto \sigma^{\prime}(\mathrm{y})\right]}
$$

where $\llbracket \mathrm{E} \rrbracket \sigma$ denotes E 's value with $\sigma$, and $\mathrm{x} \mapsto v$ assigns $v$ to x .
Example:

$$
\begin{aligned}
& \text { func } g(x) \text { local } z ; z=x+1 \\
& a=g(2) ; b=g(a) ; a=a * b
\end{aligned}
$$



The derivation tree naturally separates the calling contexts.

## Recursions (*) force accelerated termination (!):

 func fac(a) local b; if $\mathrm{a}=0(\mathrm{~b}=1)(\mathrm{b}=\mathrm{fac}(\mathrm{a}-1) ; \mathrm{b}=\mathrm{a} * \mathrm{~b})$ $c=\mathrm{fac}(3)$
$X=\langle 0,1\rangle \sqcup\langle T, T * X . b\rangle$ The least solution sets $X=\langle T, T\rangle$.

## The traditional data-flow implementation uses call strings:

- Each procedure has its own control-flow graph, as does the main program. Each procedure invocation and return is drawn as a "goto" arc in the graph for the entire program.
- When the program is analyzed, the store is accompanied by a calling history, called the call string. (E.g., main calls p-the call string is "main::p".)
- A finite bound, $k$, is placed on the call string's length - only the the $k$ most recent invocations are remembered.
- Say that the call string is $S$, execution is in $p$, and $p$ calls $q$. The call string is revised to $S^{\prime}=(S:: p) \downarrow k$, and q's activation record labelled $S^{\prime}$ is used to execute q. At conclusion, control returns to S.last - p - and the call string is shortened. (If the call string is empty, then the return "gos to" all possible return points!)


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