

# Localizing Widening and Narrowing

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(joint work with Francesca Scozzari)

We will show two techniques to **improve precision in AI-based static analysis on nested loops**:

**Localized widening** restricts the scope of application of widening

**Localized narrowing** intertwines ascending and descending phases for nested loops

These techniques are:

- domain independent
- compatible with other precision-improving techniques
- effective (at least for localized widening)
- new (?)

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An idea similar to *localized narrowing* has been presented yesterday, at PLDI:

K. Apinis, H. Seidl, V. Vojdani

*How to Combine Widening and Narrowing for Non-monotonic Systems of Equation*

# Abstract Interpretation and Equations

In abstract interpretation-based static analysis, the program to analyze is typically translated into a set of equations:

$$\begin{cases} x_1 = \Phi_1(x_1, \dots, x_n) \\ \vdots \\ x_n = \Phi_n(x_1, \dots, x_n) \end{cases}$$

- each  $x_i$ 
  - is the member of an **abstract domain**
  - corresponds to a program point
- each  $\Phi_i$ 
  - is an **abstract transformer**
  - corresponds to a node in the control flow graph
- we want a **post-fixpoint** (possibly the least fixpoint) of this system

# How to get non-trivial post-fixpoints

Several techniques:

- standard Kleene iteration
  - may not terminate if the domain is infinite
  - may be slow for finite domains
- policy/strategy iteration
  - powerful technique but only for template domains
- acceleration
  - powerful technique but only for restricted linear assignments
- widening/narrowing

Widening is generally applicable:

- ascending phase using a **widening** operator which ensures convergence
- an optional descending phase to improve the result

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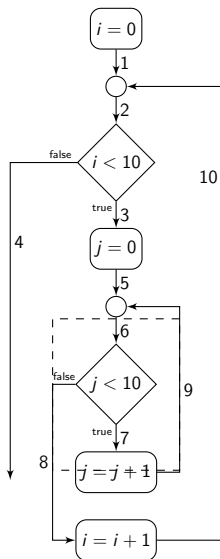
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# From programs to equations

```
i = 0
while (i < 10) {
  j = 0
  while (j < 10)
    j = j + 1
  i = i + 1
}
```



$$x_1 = [0, 0] \times [-\infty, \infty]$$

$$x_2 = x_1 \vee x_{10}$$

$$x_3 = x_2 \wedge ([-\infty, 9] \times [-\infty, \infty])$$

$$x_4 = x_2 \wedge ([10, \infty] \times [-\infty, \infty])$$

$$x_5 = \mathit{first}(x_3) \times [0, 0]$$

$$x_6 = x_5 \vee x_9$$

$$x_7 = x_6 \wedge ([-\infty, \infty] \times [-\infty, 9])$$

$$x_8 = x_6 \wedge ([-\infty, \infty] \times [10, \infty])$$

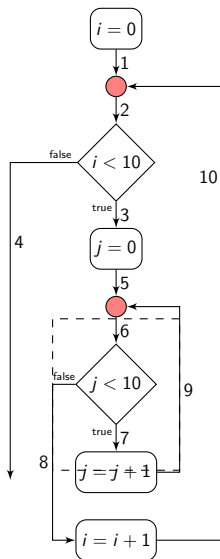
$$x_9 = x_7 + ([0, 0] \times [1, 1])$$

$$x_{10} = x_8 + ([1, 1] \times [0, 0])$$



# Introducing widening

```
i = 0
while (i < 10) {
  j = 0
  while (j < 10)
    j = j + 1
  i = i + 1
}
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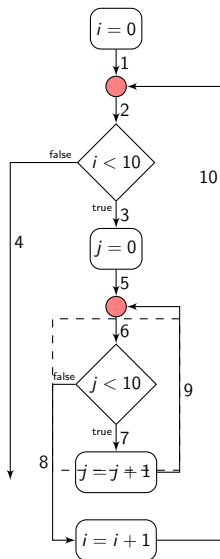
$$x_8 = x_6 \wedge ([-\infty, \infty] \times [10, \infty])$$

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$$x_1 = [0, 0] \times [-\infty, \infty]$$

$$x_2 = x_2 \nabla (x_1 \vee x_{10})$$

$$x_3 = x_2 \wedge ([-\infty, 9] \times [-\infty, \infty])$$

$$x_4 = x_2 \wedge ([10, \infty] \times [-\infty, \infty])$$

$$x_5 = \text{first}(x_3) \times [0, 0]$$

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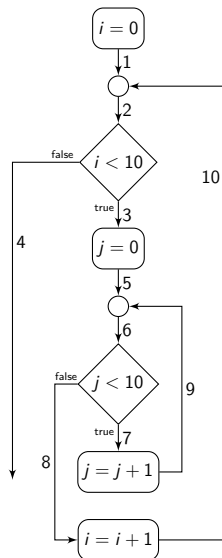
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# Problems with nested loops

## Ascending chain



$$x_1 = \perp$$

$$x_2 = \perp$$

$$x_3 = \perp$$

$$x_4 = \perp$$

$$x_5 = \perp$$

$$x_6 = \perp$$

$$x_7 = \perp$$

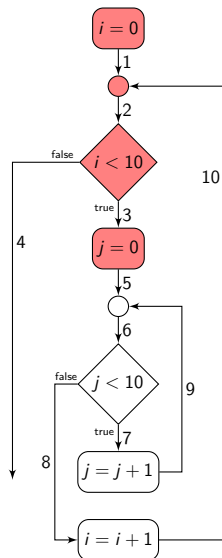
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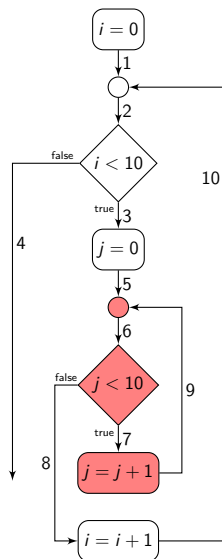
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$$x_6 = \{i = 0, 0 \leq j\}$$

$$x_7 = \{i = 0, 0 \leq j \leq 9\}$$

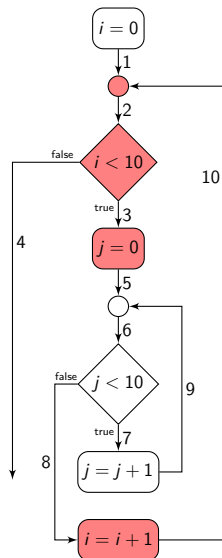
$$x_8 = \{i = 0, 10 \leq j\}$$

$$x_9 = \{i = 0, 1 \leq j \leq 10\}$$

$$x_{10} = \perp$$

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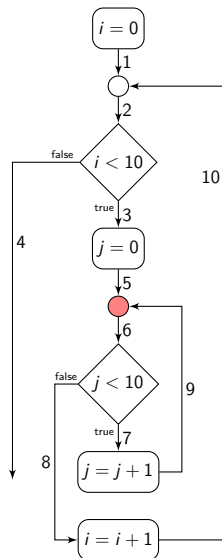
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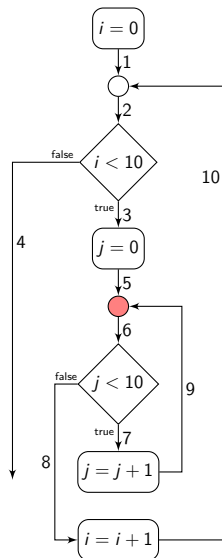
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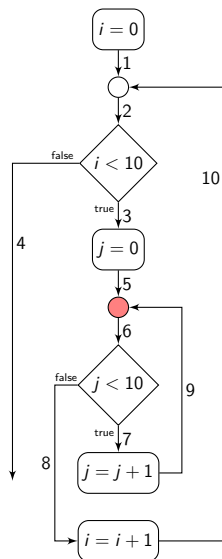
$$x_{10} = \{i = 1, 10 \leq j\}$$

$$x_6 = \{i = 0, 0 \leq j\} \nabla \{0 \leq i \leq 9, 0 \leq j \leq 10\}$$



# Problems with nested loops

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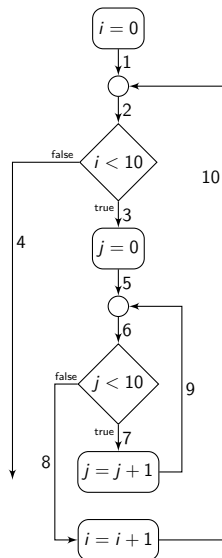
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# Problems with nested loops

## Result of ascending chain



$$x_1 = \{i = 0\}$$

$$x_2 = \{0 \leq i\}$$

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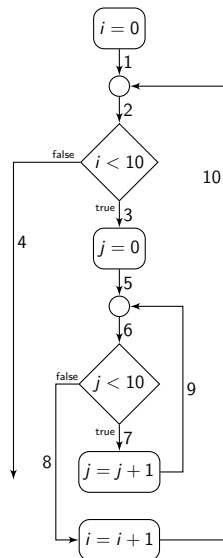
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# Problems with nested loops

Result of descending chain



$$x_1 = \{i = 0\}$$

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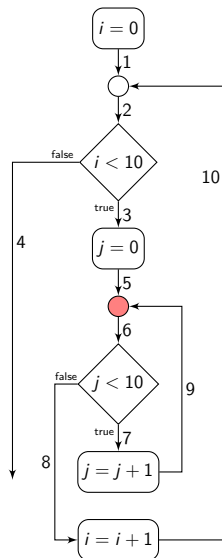
$$x_9 = \{0 \leq i, 1 \leq j \leq 10\}$$

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We cannot prove  $i = 10$  in  $x_4$

# Problems with nested loops

## A step back



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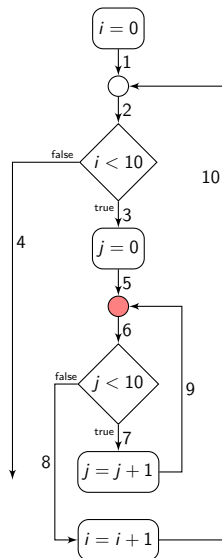
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$$x_6 = x_6 \nabla (x_5 \cup x_9)$$

# Localized widening

What is localized widening?



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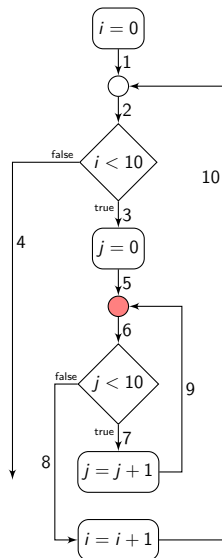
$$x_9 = \{i = 0, 1 \leq j \leq 10\}$$

$$x_{10} = \{i = 1, 10 \leq j\}$$

$$x_6 = x_6 \nabla (x_5 \cup x_9) \implies x_6 = x_5 \cup (x_6 \nabla x_9)$$

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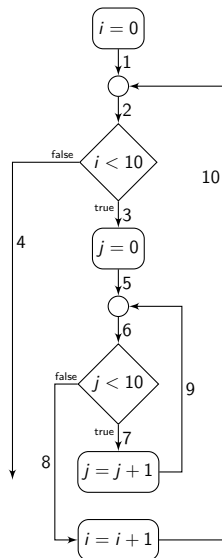
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# Localized widening

Result of ascending chain with localized widening



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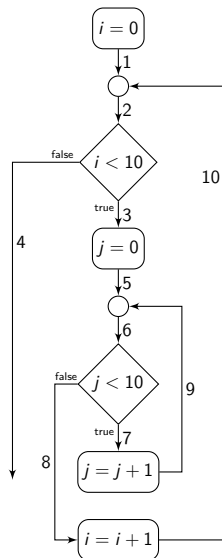
$$x_8 = \{0 \leq i \leq 9, 10 \leq j\}$$

$$x_9 = \{0 \leq i \leq 9, 1 \leq j \leq 10\}$$

$$x_{10} = \{1 \leq i \leq 10, 10 \leq j\}$$

# Localized widening

Result of descending chain with localized widening



$$x_1 = \{i = 0\}$$

$$x_2 = \{0 \leq i \leq 10\}$$

$$x_3 = \{0 \leq i \leq 9\}$$

$$x_4 = \{10 \leq i \leq 10\}$$

$$x_5 = \{0 \leq i \leq 9, j = 0\}$$

$$x_6 = \{0 \leq i \leq 9, 0 \leq j \leq 10\}$$

$$x_7 = \{0 \leq i \leq 9, 0 \leq j \leq 9\}$$

$$x_8 = \{0 \leq i \leq 9, 10 \leq j \leq 10\}$$

$$x_9 = \{0 \leq i \leq 9, 1 \leq j \leq 10\}$$

$$x_{10} = \{1 \leq i \leq 10, 10 \leq j \leq 10\}$$

We can prove  $i = 10$  in  $x_4$



## Definition (informal)

We call *localized widening* the use of a widening in the form

$$x_i = x_{in} \vee (x_i \nabla x_{back})$$

instead of

$$x_i = x_i \nabla (x_{in} \vee x_{back})$$

where

- $x_{in}$  is the value of the edge(s) coming from the outer component;
- $x_{back}$  is the value of the back edge(s) of the loop.

## Theorem

*Using localized widening, every chaotic iteration sequence terminates on a post-fixpoint (if every loop head is a widening point).*

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The optimization given by localized widening is very very simple. Is it really new?

We cannot be sure it has not been implemented before, but we think it has not been described before.

We are sure both `INTERPROC` and `PAGAI` do not implement localized widening.

We implemented it in `RANDOM` long before this paper.

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# Is it really worth

Is it really worth to implement it? **Definitively yes.**

- It is very simple.  
Our implementation in PAGAI, apart from stuff related to configuration and user interface, only requires to change a single line of code.
- Nested loops are common.  
Most programs benefits from the improved precision.
- Computational overhead should be negligible.  
Hard to say something more precise, due to non-monotonicity of widening.

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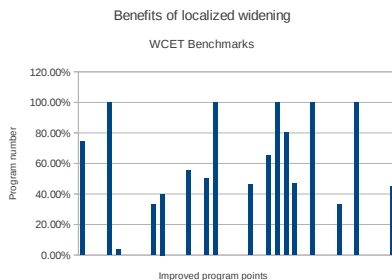
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# Experiments

## Comaprison with standard widening

We implemented localized widening in Pagai and compared it with standard widening.



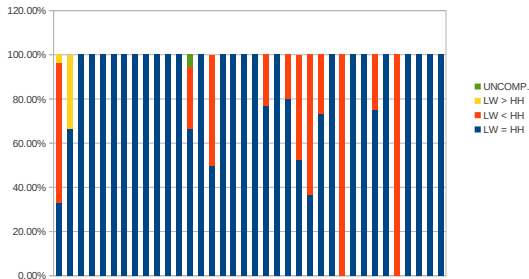
- total: 379 nodes, improvements in 164 nodes
- standard widening: 4.48 secs, 19522 asc. steps and 23415 desc. steps
- localized widening: 5.22 secs, 19363 asc. steps and 22528 desc. steps

# Experiments

## Comparison with Halbwachs & Henry (SAS '12)

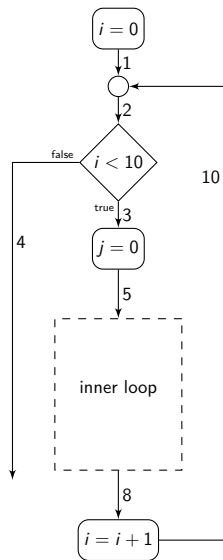
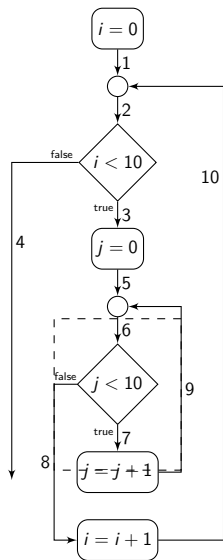
Comparison of localized widenings and HH optimization

WCET Benchmarks

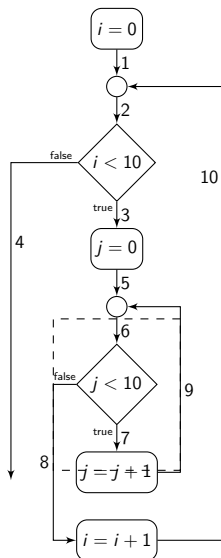


- 91 improved head nodes, 2 regressed, 2 incomparable
- localized widening: 5.26 secs, 19363 asc. steps and 22528 desc. steps
- hh narrowing: 5.88 secs, 22665 asc. steps and 27134 desc. steps

# Loops as black boxes

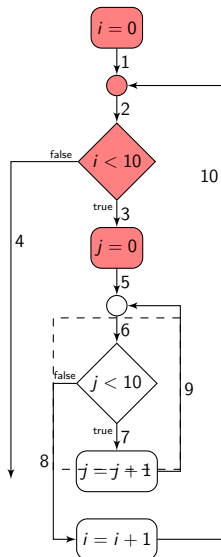


# Iteration with localized narrowing



$x_1 = \perp$   
 $x_2 = \perp$   
 $x_3 = \perp$   
 $x_4 = \perp$   
 $x_5 = \perp$   
 $x_6 = \perp$   
 $x_7 = \perp$   
 $x_8 = \perp$   
 $x_9 = \perp$   
 $x_{10} = \perp$

# Iteration with localized narrowing



$$x_1 = \{i = 0\}$$

$$x_2 = \{i = 0\}$$

$$x_3 = \{i = 0\}$$

$$x_4 = \perp$$

$$x_5 = \{i = 0, j = 0\}$$

$$x_6 = \perp$$

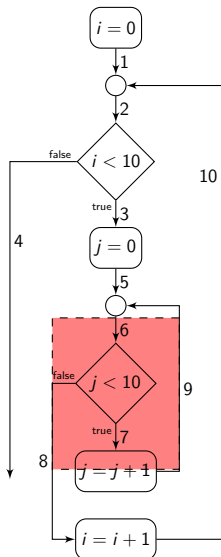
$$x_7 = \perp$$

$$x_8 = \perp$$

$$x_9 = \perp$$

$$x_{10} = \perp$$

# Iteration with localized narrowing



$$x_1 = \{i = 0\}$$

$$x_2 = \{i = 0\}$$

$$x_3 = \{i = 0\}$$

$$x_4 = \perp$$

$$x_5 = \{i = 0, j = 0\}$$

$$x_6 = \{i = 0, 0 \leq j \leq 10\}$$

$$x_7 = \{i = 0, 0 \leq j \leq 9\}$$

$$x_8 = \{i = 0, j = 10\}$$

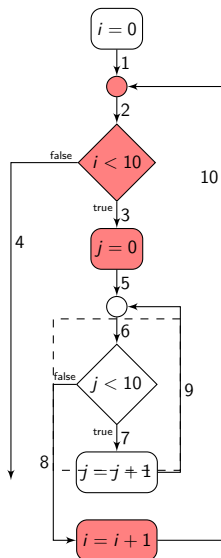
$$x_9 = \{i = 0, 1 \leq j \leq 10\}$$

$$x_{10} = \perp$$

Ascending and descending chain



# Iteration with localized narrowing



$$x_1 = \{i = 0\}$$

$$x_2 = \{0 \leq i\}$$

$$x_3 = \{0 \leq i \leq 9\}$$

$$x_4 = \{10 \leq i\}$$

$$x_5 = \{0 \leq i \leq 9, j = 0\}$$

$$x_6 = \{i = 0, 0 \leq j \leq 10\}$$

$$x_7 = \{i = 0, 0 \leq j \leq 9\}$$

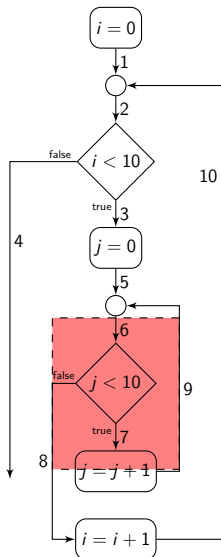
$$x_8 = \{i = 0, j = 10\}$$

$$x_9 = \{i = 0, 1 \leq j \leq 10\}$$

$$x_{10} = \{i = 1, j = 10\}$$

What to do with  $x_6 - x_9$ ?

# Iteration with localized narrowing



$$x_1 = \{i = 0\}$$

$$x_2 = \{0 \leq i\}$$

$$x_3 = \{0 \leq i \leq 9\}$$

$$x_4 = \{10 \leq i\}$$

$$x_5 = \{0 \leq i \leq 9, j = 0\}$$

$$x_6 = \perp$$

$$x_7 = \perp$$

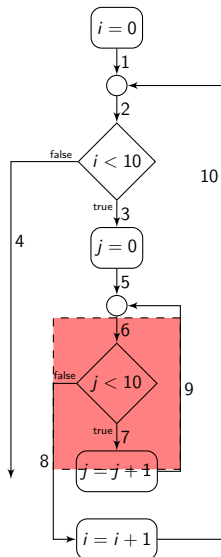
$$x_8 = \perp$$

$$x_9 = \perp$$

$$x_{10} = \{i = 1, j = 10\}$$

Start with  $x_6 = x_7 = x_8 = x_9 = \perp \dots$

# Iteration with localized narrowing



$$x_1 = \{i = 0\}$$

$$x_2 = \{0 \leq i\}$$

$$x_3 = \{0 \leq i \leq 9\}$$

$$x_4 = \{10 \leq i\}$$

$$x_5 = \{0 \leq i \leq 9, j = 0\}$$

$$x_6 = \{0 \leq i \leq 9, 0 \leq j \leq 10\}$$

$$x_7 = \{0 \leq i \leq 9, 0 \leq j \leq 9\}$$

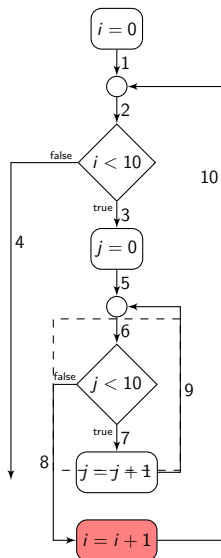
$$x_8 = \{0 \leq i \leq 9, j = 10\}$$

$$x_9 = \{0 \leq i \leq 9, 1 \leq j \leq 10\}$$

$$x_{10} = \{i = 1, j = 10\}$$

... and re-analyze

# Iteration with localized narrowing



$$x_1 = \{i = 0\}$$

$$x_2 = \{0 \leq i\}$$

$$x_3 = \{0 \leq i \leq 9\}$$

$$x_4 = \{10 \leq i\}$$

$$x_5 = \{0 \leq i \leq 9, j = 0\}$$

$$x_6 = \{0 \leq i \leq 9, 0 \leq j \leq 10\}$$

$$x_7 = \{0 \leq i \leq 9, 0 \leq j \leq 9\}$$

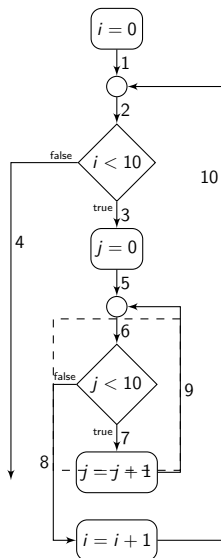
$$x_8 = \{0 \leq i \leq 9, j = 10\}$$

$$x_9 = \{0 \leq i \leq 9, 1 \leq j \leq 10\}$$

$$x_{10} = \{1 \leq i \leq 10, j = 10\}$$

End of external ascending sequence

# Iteration with localized narrowing



$$x_1 = \{i = 0\}$$

$$x_2 = \{0 \leq i \leq 10\}$$

$$x_3 = \{0 \leq i \leq 9\}$$

$$x_4 = \{i = 10\}$$

$$x_5 = \{0 \leq i \leq 9, j = 0\}$$

$$x_6 = \{0 \leq i \leq 9, 0 \leq j \leq 10\}$$

$$x_7 = \{0 \leq i \leq 9, 0 \leq j \leq 9\}$$

$$x_8 = \{0 \leq i \leq 9, j = 10\}$$

$$x_9 = \{0 \leq i \leq 9, 1 \leq j \leq 10\}$$

$$x_{10} = \{1 \leq i \leq 10, j = 10\}$$

End of external descending sequence

# Localized widening vs localized narrowing

In this case, both techniques give the same result, but in general?  
Due to non-monotonicity, it is difficult to actually prove something, but in general, localized narrowing is more precise.

```
i = 0
while (TRUE) {
  i = i+1
  j = 0
  while (j < 10) {
    // Inv:  $0 \leq i \leq 10$ 
    j = j+1
  }
  if (i > 9) i = 0
}
```

*Localized narrowing* proves  
the required invariant

*Localized widening* doesn't  
because the check for the  
upper bound of  $i$  is after the  
inner loop.

When we restart the analysis of an inner loop, which values to choose for the data flow variables ?

- RESTART policy: start from  $\perp$  (the one we used in the example)
- CONTINUE policy: start from last values
- HYBRID policy:
  - behave as CONTINUE if outer loop is in ascending phase;
  - behave as RESTART if outer loop is in descending phase

# Problems with CONTINUE policy

The CONTINUE policy is faster, but less precise.

```
i = 0
while (TRUE) {
  i = i+1
  j = 0
  while (j < 10) {
    // Inv:  $0 \leq i \leq 10$ 
    j = j+1
  }
  if (i > 9) i = 0
}
```

*RESTART* policy proves the required invariant

*CONTINUE* policy doesn't because the check for the upper bound of  $i$  is after the inner loop.



When we restart the analysis of an inner loop, which values to choose for the data flow variables ?

- RESTART policy: start from  $\perp$  (the one we used in the example)
- CONTINUE policy: start from last values
- HYBRID policy:
  - behave as CONTINUE if outer loop is in ascending phase;
  - behave as RESTART if outer loop is in descending phase

*Localized widening* works for any iteration strategy.

*Localized narrowing* is based on a recursive iteration strategy as defined in Burdoncle '93 but:

- different loops may be in different phases
- for two nested loops, all possible combinations of ascending and descending phases are possible

- We have implemented localized narrowing in our analyzer JANDOM
  - JANDOM is an abstract interpreter for Java bytecode and other languages (<https://github.com/jandom-devel/Jandom>)
  - ...but it is not yet ready to analyze real code
- Localized narrowing has not been implemented in PAGAI
- ... hence, we have only limited qualitative comparison of precision with other techniques

# Four programs

## nested

---

```
i = 0
while (i < 10) {
  j = 0
  while (j < 10)
    j = j + 1
  i = i + 1
}
// Inv: i = 10
```

## hh (Halbwachs & Henry)

---

```
i = 0
while (i < 4) {
  j = 0
  while (j < 4) {
    // Inv: i ≤ j + 3
    i = i + 1
    j = j + 1
  }
  i = i - j + 1
}
```

## hybrid

---

```
i = 0
while (TRUE) {
  i = i + 1
  j = 0
  while (j < 10)
    // Inv: 0 ≤ i ≤ 10
    j = j + 1
  if (i > 9) i = 0
}
```

## nested2

---

```
i = 0
while (TRUE) {
  // Inv: i ≥ 0
  j = 0
  while (j < 10) {
    j = j + 1
  }
  i = i + 11 - j
}
```

# Results on the four programs

program	loc widening	continue	hybrid	guided	lookahead	HH
nested	yes	yes	yes	no	no	yes
nested2	no	yes	yes	no	yes	no
hybrid	no	no	yes	no	no	yes
hh	yes	no	yes	no	no	yes

**loc widening** localized widening

**continue** localized narrowing with CONTINUE policy

**hybrid** localized narrowing with HYBRID policy

**guided** guided static analysis

**lookahead** lookahead widening

**HH** optimized narrowing in Halbwachs & Henry 2012

- ① *localized widening*: do not see any reason not to implement it
  - easy to implement
  - good precision improvement
  - low overhead
- ② *localized narrowing*: more work needed to establish its usefulness
  - implementation from easy (for AST-based analyzers) to medium difficulty
  - better than localized widening, but how much better?
  - what overhead?

Results in PLDI '13 paper by Apinis, Seidl, Vojdani are encouraging.

- 1 Evaluate benefits of localized narrowing
  - Implement localized narrowing in PAGAI
  - Finish implementation of Java bytecode analysis in JANDOM
- 2 Merge ideas from this paper and the PLDI '13 paper by Apinis, Seidl, Vojdani.