Code-based Testing with Constraints

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HUAWEI, Paris, 31 Mar. 2021

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VIAS: Validation Intelligence of Autonomous Software Systems

Organized as a **Research-Based Innovation Center** until Dec. 2019

Certus
Centre for Software Verification & Validation

Strongly involved into the **AI4EU Project** (H2020, 2019-2021)
European AI-on-demand platform
and the **TRANSACT Project** (ECSEL, 2021-2024)

AI4EU

Created **RESIST**, the first Inria-Simula associate team in 2021

Inria

The Research Council of Norway

THE FRAMEWORK PROGRAMME FOR RESEARCH AND INNOVATION
HORIZON 2020

simula consulting

Outline

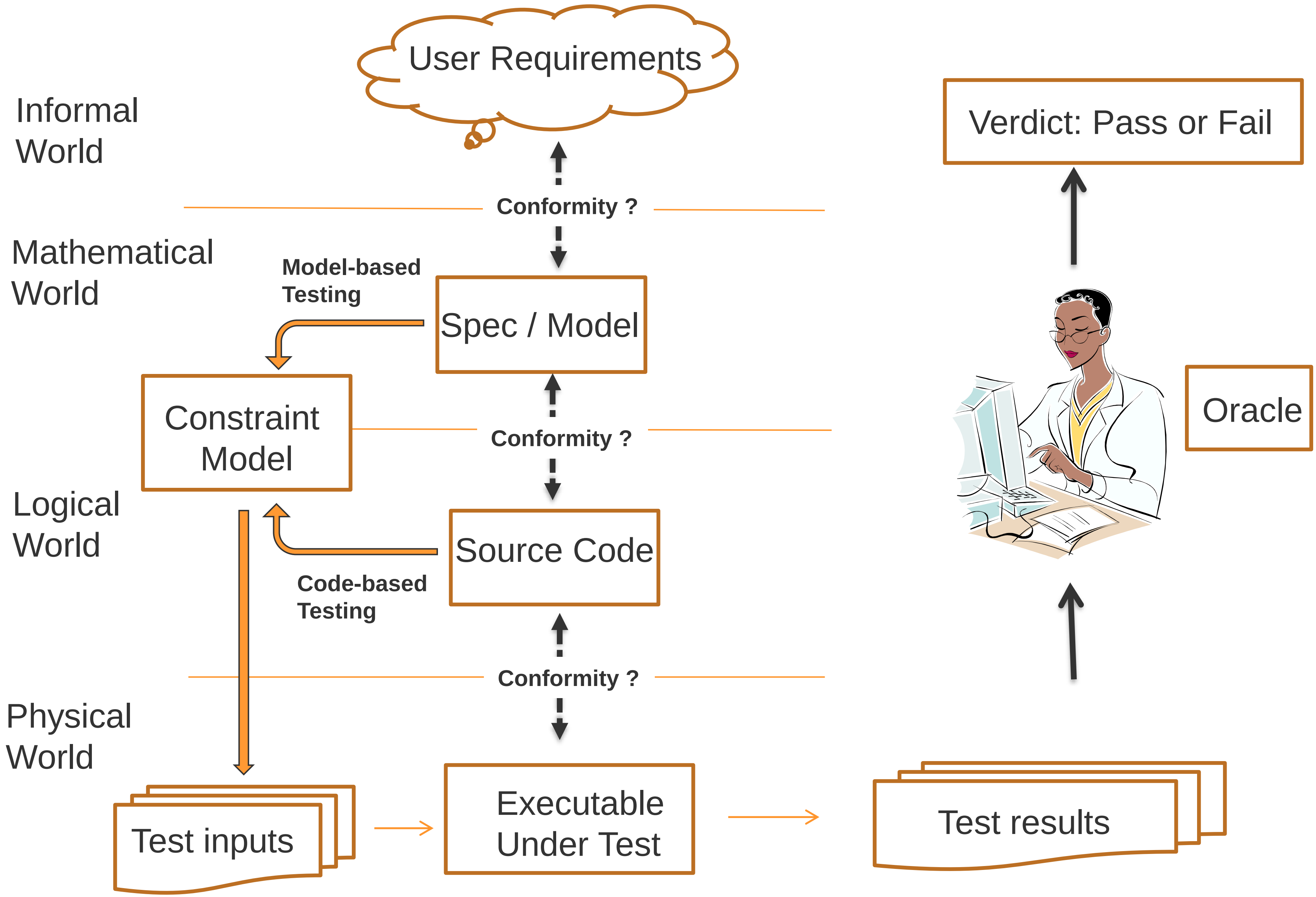
Software Testing and Code-based Testing

Path-oriented exploration

Constraint-based exploration

Summary and further work

Software Testing



Code-based Testing

Code-based testing aims at generating test inputs such that selected code locations are executed

Test inputs generation is a **cognitively complex task**:
- Requires to "understand" the code in order to find test inputs
- Program's input space is usually very large (sometimes unbounded)
- Complex software code (e.g., solving ODEs or PDEs) are difficult to test
- Code optimizations can often only be tested with code-based testing

Not easily amenable to automation:
- Automatic test inputs generation is undecideable in the general case!
- Exploring the input space yields to combinatorial explosion
- Control and data structures requires dedicated treatments

The automatic test input generation problem

Given a location k in a program under test, generate a test input that reaches k

Undecidable in general, but ad-hoc methods exist

$f\ (int\ x_1, int\ x_2, int\ x_3)\ \{$

$if(x_1 == x_2\ \&\&\ x_2 == x_3)$

$if(x_3 == x_1 * x_2)\ \ldots$

location k

Here, with random testing, Prob{ reack k} = 2 over $2^{32} \times 2^{32} \times 2^{32}$ = $\mathbf{2^{-95} = 0.00000\ldots1}$

So, constraint solving is crucial to address this problem in an efficient way

- ✓ Loops and non-feasible paths
- ✓ Modular integer and floating-point computations
- ✓ Pointers, dynamic structures, function calls, …
- ✓ Inheritance, polymorphism

Constraint-Based Testing (CBT)

Constraint-Based Testing (CBT) is the process of **generating test cases** against a **testing objective** by using **constraint solving techniques**

Introduced 30 years ago by Offut and DeMillo in
Constraint-based automatic test data generation IEEE TSE 1991

An overview is available in
Constraint-Based Testing: An Emerging Trend in Software Testing by Gotlieb
In Advances in Computers, 67-101 Academic Press ed. Vol. 99. Elsevier, 2015

Success stories in the context of code-based testing with code coverage objectives (Microsoft, CEA, Smartesting, Conformiq, Thales, …)

Lots of Research works and tools !

Outline

- Software Testing and Code-based Testing
- Path-oriented exploration
- Constraint-based exploration
- Summary and further work

Path-oriented test data generation

Select one or several paths → 1. **Path selection**

Generate the path conditions → 2. **Symbolic evaluation**

Solve the path conditions to generate test data that activate the selected paths
→ 3. **Constraint solving**

<u>Test objectives:</u>

generating a test suite that covers a given testing criterion

(all-statements, all-decisions, all-paths…)

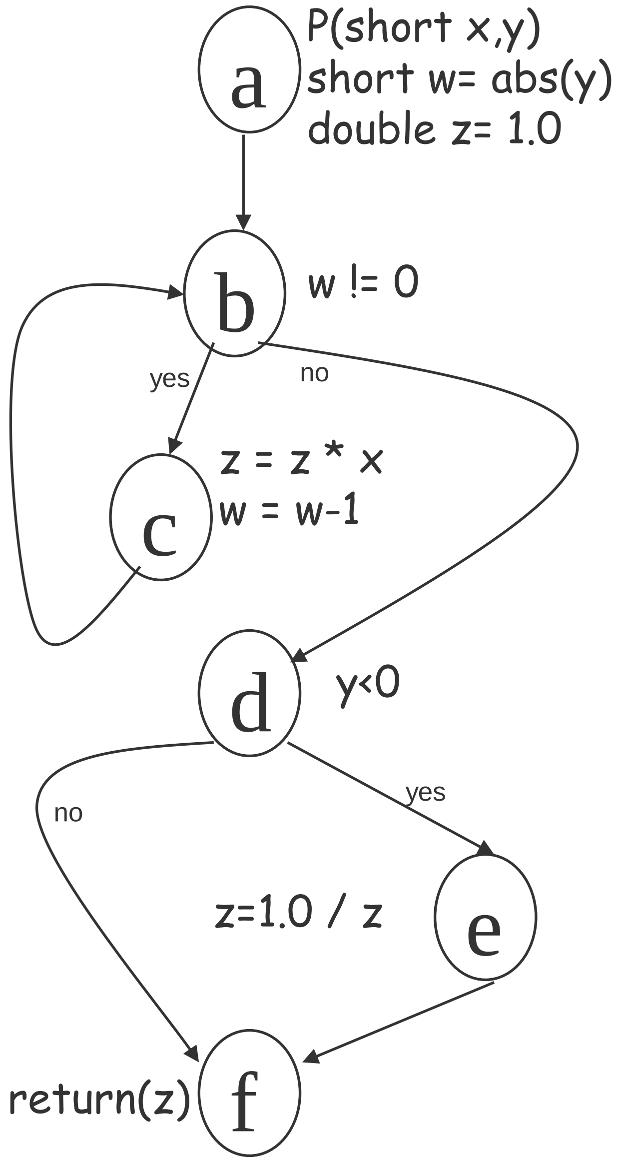
or a test data that raise a safety or security problem

(assertion violation, buffer overflow, …)

Main CBT tools: **ATGen** (Meudec 2001), **EXE** (Cadar 2006)
ECLAIR (Bagnara 2013), **BINSEC** (Bardin 2015, 2020)

Path selection on an example

```
double P(short x, short y) {
      short   w = abs(y) ;
      double z  = 1.0 ;
      while ( w != 0 )
      {
         z  = z * x ;
         w = w - 1 ;
      }
      if ( y<0 )
       z = 1.0 / z ;
    return(z) ;
    }
```



Path selection on an example

<u>all-statement coverage:</u>

a-b-c-b-d-e-f

<u>All-decisions coverage:</u>

a-b-c-b-d-e-f

a-b-d-f

<u>all-2-paths (at most 2 times in loops):</u>

a-b-d-f

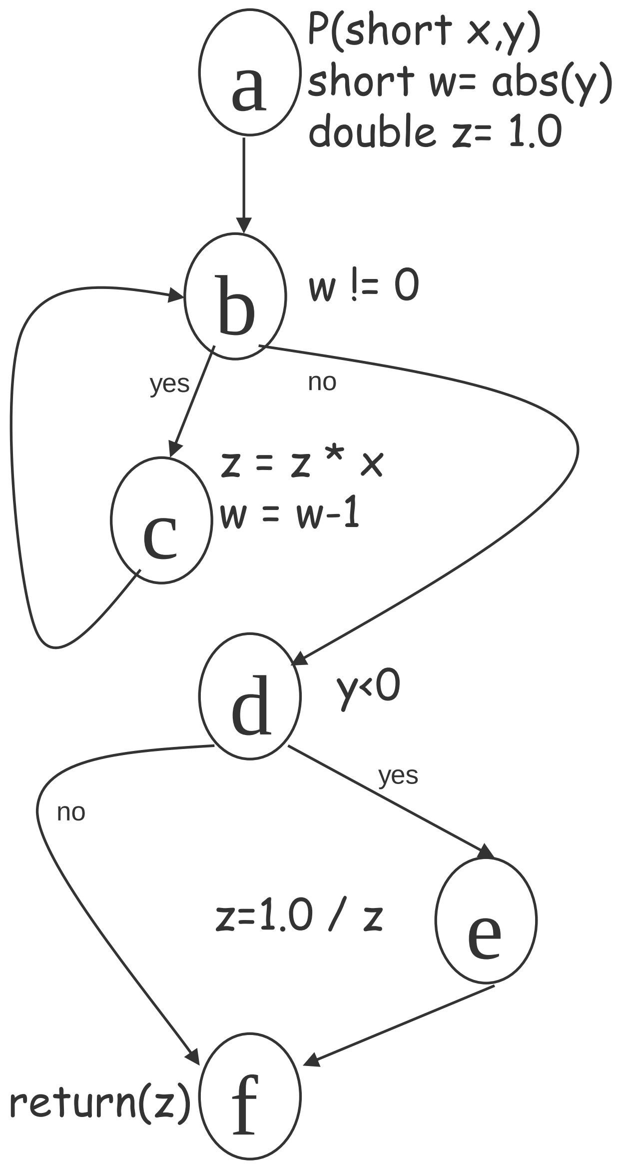
~~a-b-d-e-f~~

…

a-b-(c-b)^2-d-e-f

<u>all-paths:</u>

Impossible



Path condition generation

Symbolic state: <Path, State, Path Conditions>

Path = n_i-..-n_j is a path expression of the CFG

State = $<v_i,\varphi_i>_{v \in Var(P)}$ where φ_i is an algebraic expression over **X**

Path Cond. = $c_1,..,c_n$ where c_i is a condition over **X**

X denotes symbolic variables associated to the program inputs and Var(P) denotes internal variables

Symbolic execution

<u>Ex :</u> a-b-(c-b)^2-d-f with X,Y

<a, <z,1.>, <w,abs(Y)>, true >

<a-b, <z,1.>, <w,abs(Y)>, abs(Y) != 0 >

<a-b-c, <z,X>, <w,abs(Y)-1>, abs(Y) != 0 >

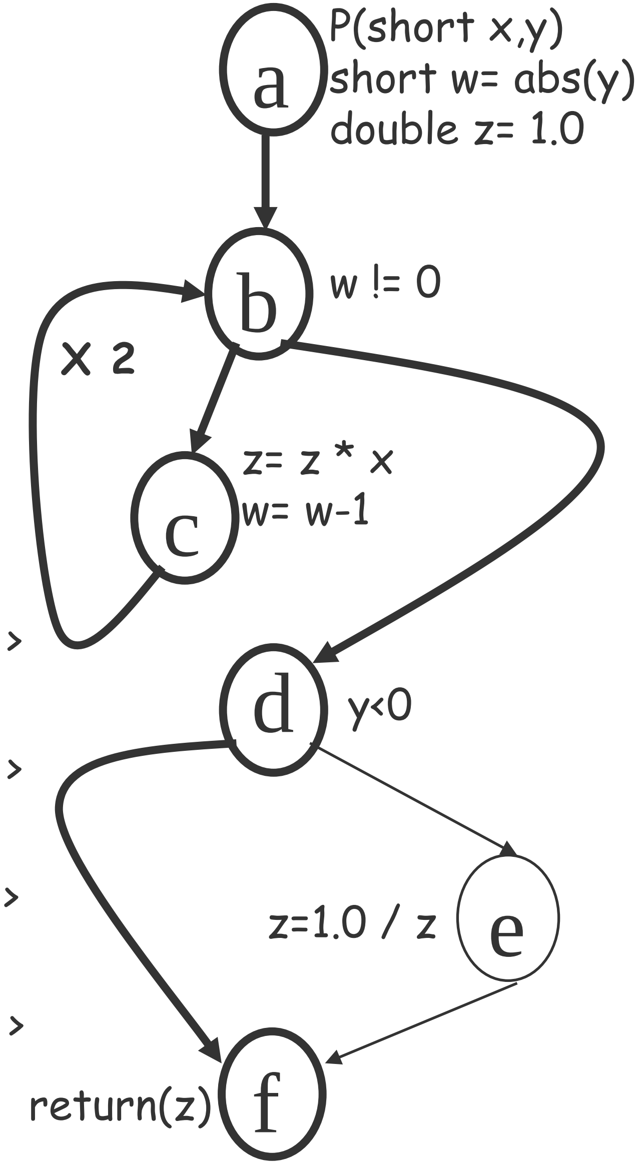
<a-b-c-b, <z,X.>, <w,abs(Y)-1>,
abs(Y) != 0, abs(Y)-1 != 0 >

< a-b-c-b-c, <z,X^2>, <w,abs(Y)-2>,
abs(Y) != 0, abs(Y)-1 != 0 >

<a-b-(c-b)^2, <z,X^2>, <w,abs(Y)-2>,
abs(Y) != 0, abs(Y) != 1, abs(Y)-2 = 0 >

<a-b-(c-b)^2-d, <z,X^2>, <w,abs(Y)-2>,
abs(Y) != 0, abs(Y) != 1, abs(Y) = 2, Y $\geq$ 0 >

<a-b-(c-b)^2-d-f, <z,X^2>, <w,0>, Y=2 >



Computing symbolic states

- <Path, State, PC> is computed by induction over each statement of Path

- When the Path conditions are unsatisfiable then Path is non-feasible and reciprocally (i.e., symbolic execution captures the concrete semantics)

  ex : <~~a-b-d-e-f~~,{…}, **abs(Y)=0 ∧ Y<0** >

- Forward vs backward analysis:

  Forward → interesting when states are needed
  Backward → saves memory space (states are not memoized)

Backward analysis

Ex : a-b-(c-b)²-d-f with X,Y

f,d: **Y ≥0**

b: **Y ≥0**, w = 0

c: **Y ≥0**, w-1 = 0

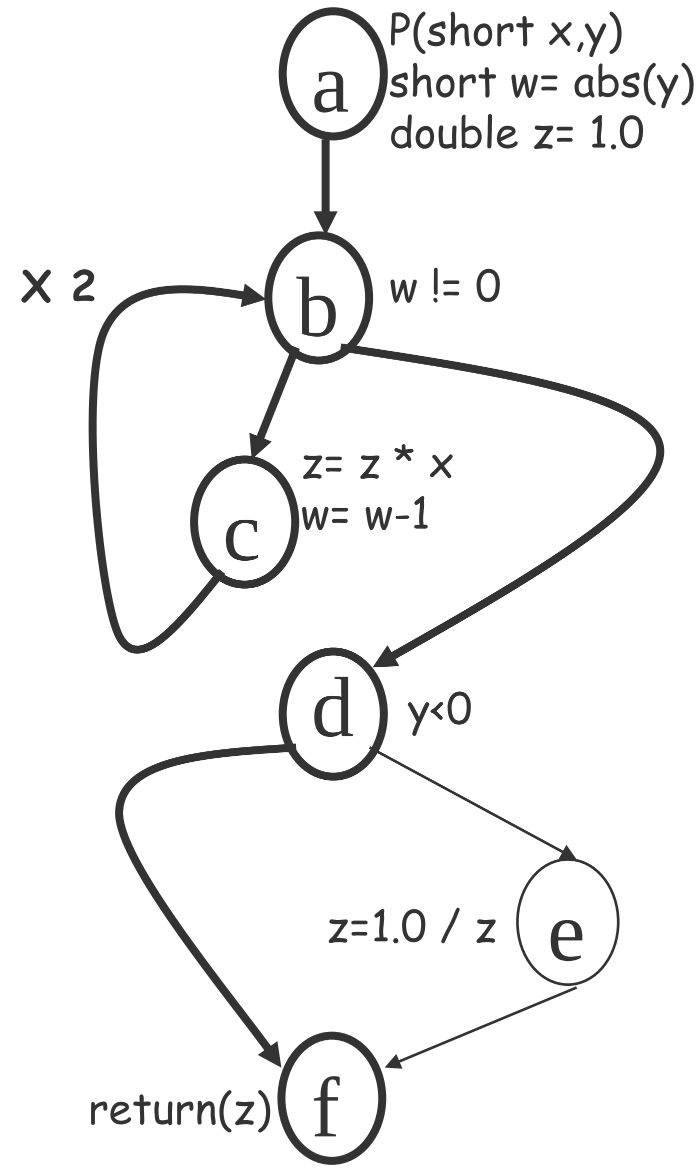
b: **Y ≥0**, w-1 = 0, w != 0

c: **Y ≥0**, w-2 = 0, w-1 != 0

b: **Y ≥0**, w-2 =0, w-1 != 0,w != 0

a: **Y ≥0, abs(Y)-2 = 0,**
abs(Y)-1 != 0, abs(Y) != 0

Y = 2



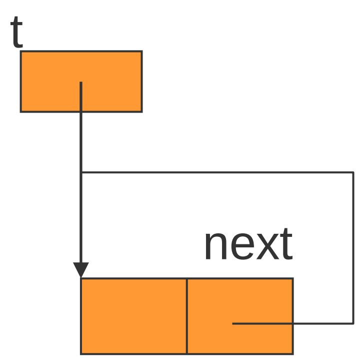
Problems for symbolic evaluation techniques

→ Combinatorial explosion of paths

→ Symbolic execution constrains the shape of dynamically allocated objects

```
int P(struct cell * t) {
   if( t == t->next ) { …
```

constrains t to:



Modelling dynamic memory management in constraint-based testing
(Charreteur, Botella, Gotlieb JSS 09)
Constraint-based test input generation for java bytecode
(Charreteur, Gotlieb ISSRE'10)

→ Floating-point computations

```
float foo( float x) {
   float y = 1.0e12, z ;
1. if( x < 10000.0 )
2.      z = x + y;
3. if( z > y)
4.      …
```

Is the path 1-2-3-4 feasible ?

Path conditions:

$x < 10000$

$x + 10^{12} > 10^{12}$

On the reals : $x \in \,]0, 10000[$

On the floats : no solution !

Conversely,

```
float foo( float x) {
   float y = 1.0e12, z ;
1. if( x > 0.0 )
2.      z = x + y;
3. if( z == y)
4.      …
```

Is the path 1-2-3-4 feasible ?

Path conditions:

$X > 0$

$X + 10^{12} = 10^{12}$

On the reals : no solution

On the floats: $X \in \,]0, 32767.99\ldots[$

Symbolic execution of floating-point computations
(Botella, Gotlieb, Michel STVR 06)

Symbolic test data generation for floating-point programs
(Bagnara, Carlier, Gori, Gotlieb ICST'13, JoC 15, TOSEM 21)

Dynamic Symbolic Evaluation

- Symbolic execution of a concrete execution (a.k.a. concolic execution)
- By using input values, **feasible paths only** are (automatically) selected
- Randomized algorithm, implemented by instrumenting each statement of P

Main CBT tools:

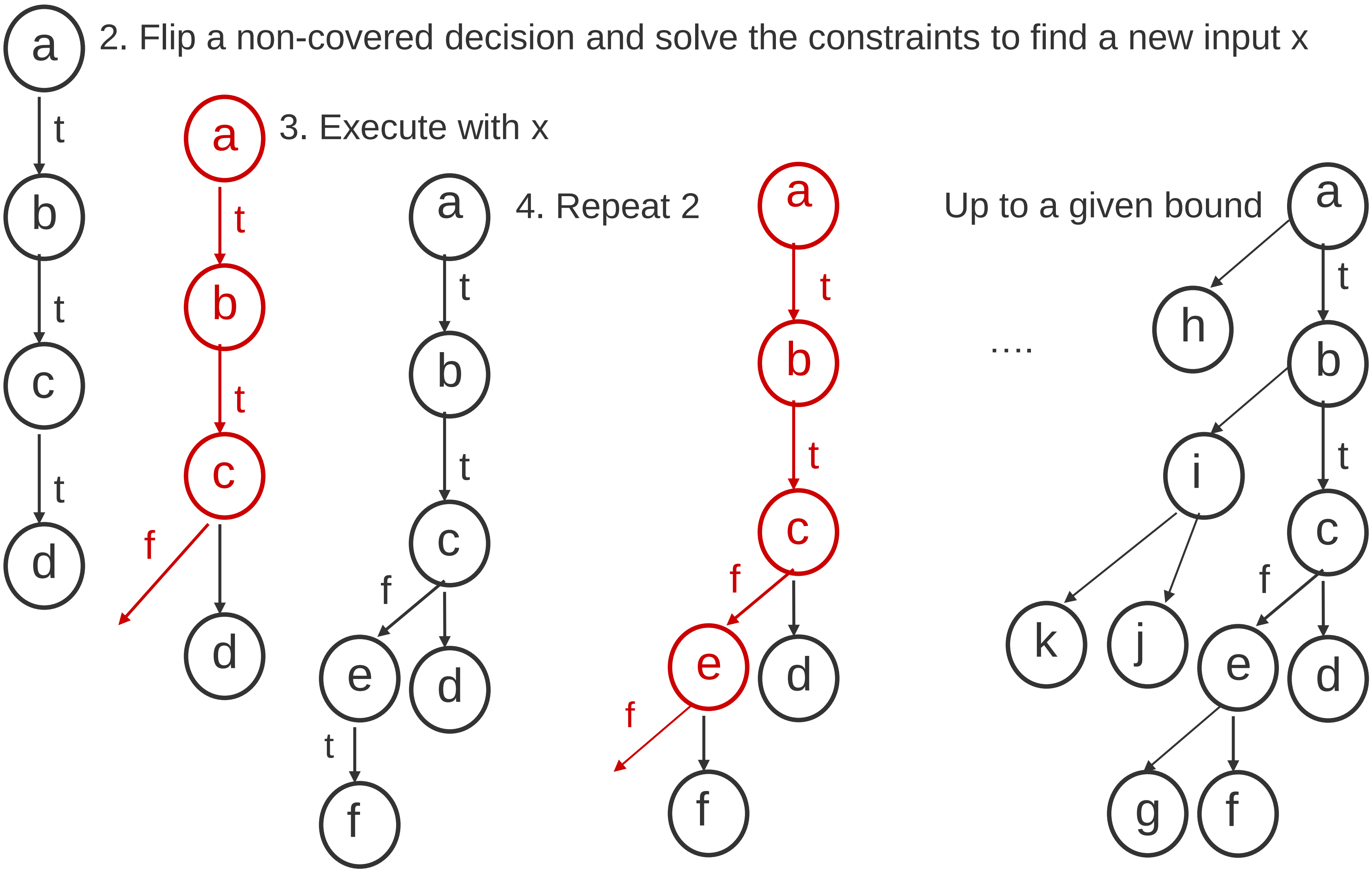
PathCrawler (Williams et al. 2005), **PEX** (Tillman et al. Microsoft 2008)
SAGE (Godefroid et al.2008), **KLEE** (Cadar, Dunbar et al. 2009)

Comes in two ingredients…

1st ingredient: path exploration

1. Draw an input at random, execute it and record path conditions
2. Flip a non-covered decision and solve the constraints to find a new input x
3. Execute with x
4. Repeat 2

Up to a given bound



2nd ingredient: use concrete values

- Use actual values to simplify the constraint set

Flip `If(` $x_3 == x_1 * x_2$) ... ($x_1 = 6, x_2=7, x_3=42$)

(1) Exact solving -- add $x_3 != x_1 * x_2$ to the constraint solver

(2) Approximate solving -- add $x_3 != 6 * x_2$ && $x_1=6$ (linear expr.)

or -- add $x_3 != x_1 * 7$ && $x_2=7$ (linear expr.)

or -- add $42 != x_1 * x_2$ && $x_3=42$ (nonlinear expr.)

(3) Approximate solving -- add $x_3 != 6 * 7$ && $x_1=6$ && $x_2=7$

(4) Useless solving -- add $42 != 6 * 7$ && $x_1=6$ && $x_2=7$ && $x_3=42$

Constraint solving in symbolic evaluation

Mixed Integer Linear Programming approaches
(i.e., simplex + Fourier's elimination + branch-and-bound)

CLP(R,Q) in ATGen (Meudec 2001)
lpsolve in DART/CUTE (Godefroid/Sen et al. 2005)

SMT-solving (= SAT + Theories)

STP in EXE and KLEE (Cadar et al. 2006, 2009)
Z3 in PEX and SAGE (Tillmann and de Halleux 2008)

Constraint Programming techniques (constraint propagation and labelling)

Colibri in PathCrawler (Williams et al. 2005)
Disolver in SAGE (Godefroid et al. 2008)
ECLAIR (Bagnara et al. 2013)

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Constraint-based program exploration

- Based on a constraint model of the whole program
  (i.e., each statement is seen as a relation between two memory states)

- Constraint reasoning over control structures

- Requires to build **dedicated constraint solvers**:
    * propagation queue management with priorities
    * specific propagators and global constraints
    * structure-aware labelling heuristics

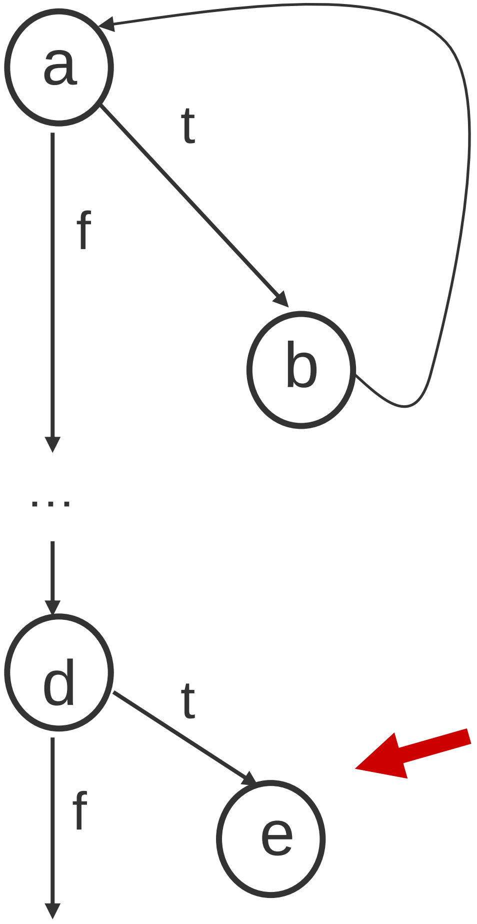
Main CBT tools: **InKa** **(**Gotlieb Botella Rueher 1998**)**,
GATEL **(**Marre 2004**)**,
Euclide (Gotlieb 2009)

A reacheability problem

```
  f(  int i  )
   {
a.     j = 100;
       while( i > 1)
b.         { j++ ; i-- ;}

    …
d. if( j > 500)
e.      …
```

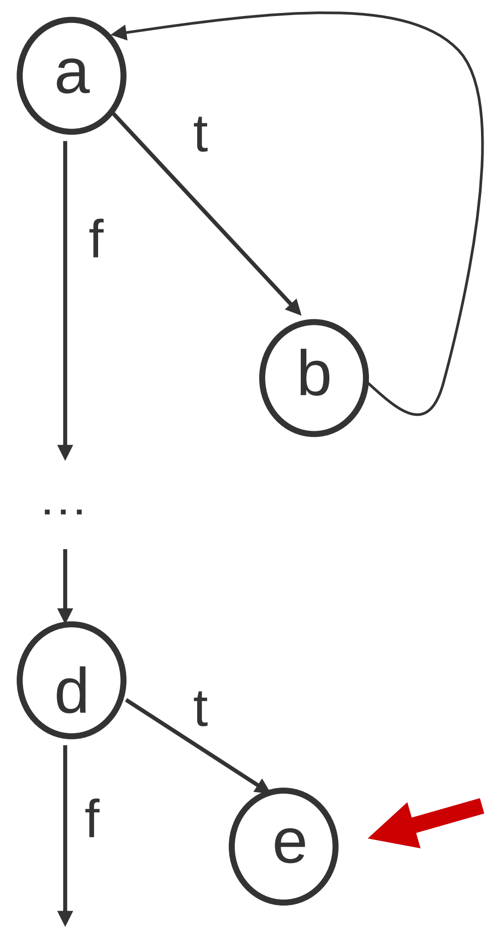
value of i to reach … ?



Path-oriented exploration

```
  f(  int i  )
   {
a.     j = 100;
       while( i > 1)
b.         { j++ ; i-- ;}

    ...
d. if( j > 500)
e.      ...
```



1. Path selection
   e.g., $(a\text{-}b)^{14}\text{-}\ldots\text{-}d\text{-}e$

2. Path conditions generation (via symbolic exec.)
   $j_1=100,\ i_1>1,\ j_2=101,\ i_2=i_1-1, \ldots j_{15}=114,\ j_{15}>500$

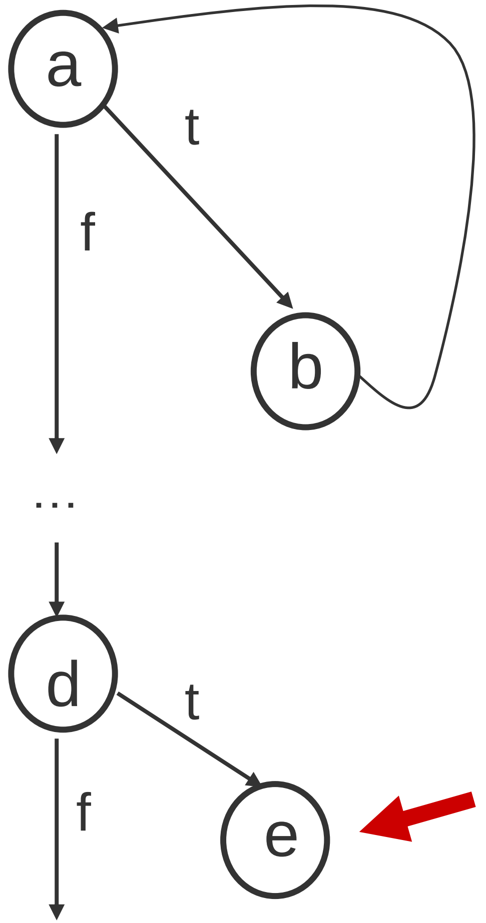
3. Path conditions solving
   unsatisfiable → FAIL

Backtrack!

Constraint-based exploration

```
 f(  int i  )
  {
a.     j = 100;
       while( i > 1)
b.         { j++ ; i-- ;}


   ...
d. if( j > 500)
e.      ...
```



1. Constraint model generation (through SSA)

2. Control dependencies generation;

   $j_1 = 100$, $i_3 \leq 1$, $j_3 > 500$

3. Constraint model solving

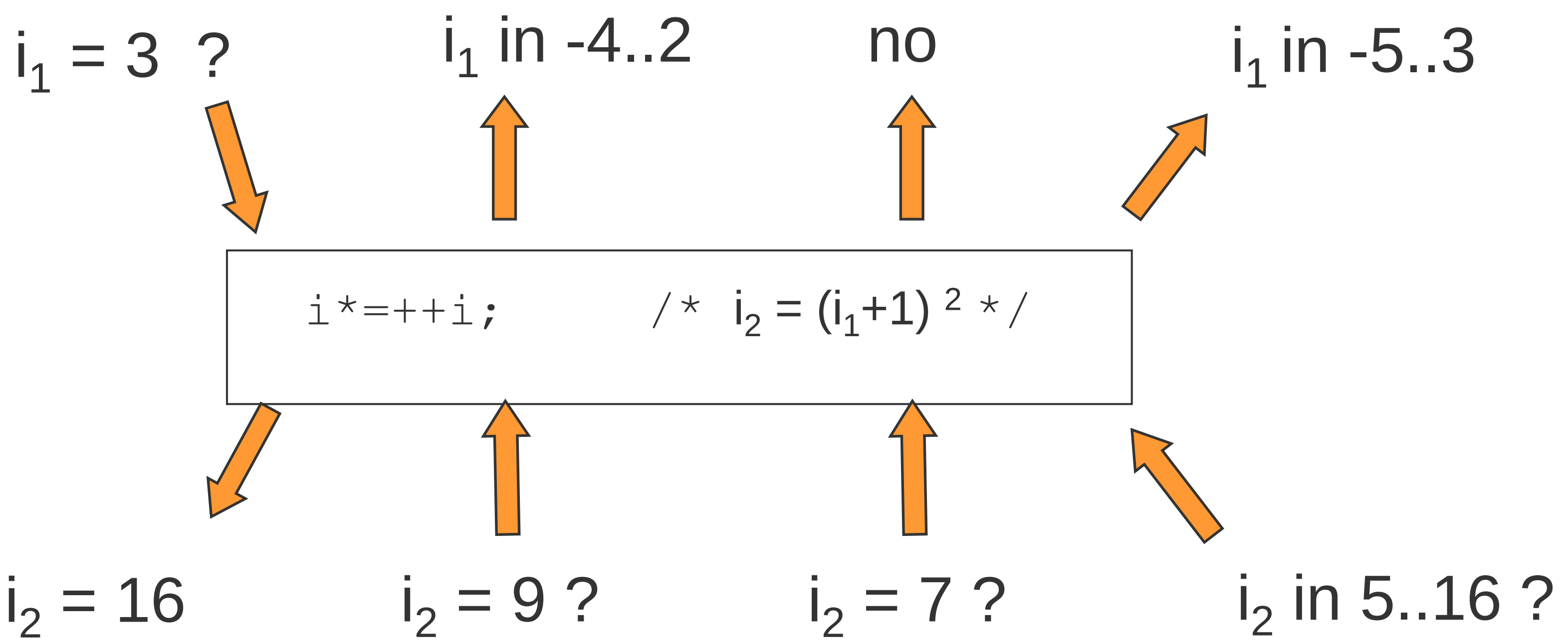
   $j_1 \neq j_3$ entailed ➔ unroll the loop 400 times ➔ i_1 in $401 .. 2^{31}-1$

No backtrack !

Assignment as Constraint

Viewing an assignment as a relation requires to normalize expressions and rename variables (through single assignment languages, e.g., SSA)

`i*=++i ;` → $i_2 = (i_1+1)^2$



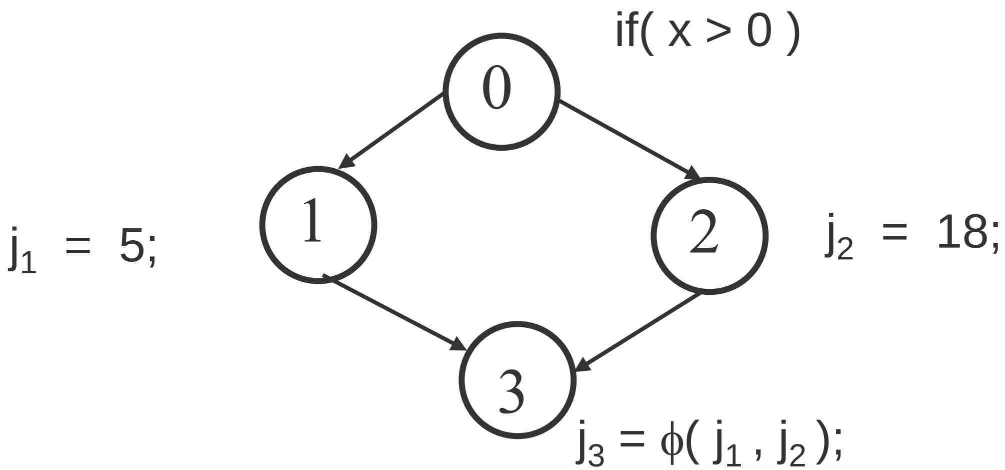
Statements as (global) constraints

- ✓ Type declaration: `signed long x;` → x in $-2^{31}..2^{31}-1$
- ✓ Assignments: `i*=++i ;` → $i_2 = (i_1+1)^2$
- ✓ Control structures: dedicated global constraints

Conditionnals (SSA) `if D then` C_1; `else` C_2; $v_3=\phi(v_1,v_2)$ → ite/6

Loops (SSA) $v_3=\phi(v_1,v_2)$ `while D do C` → w/5

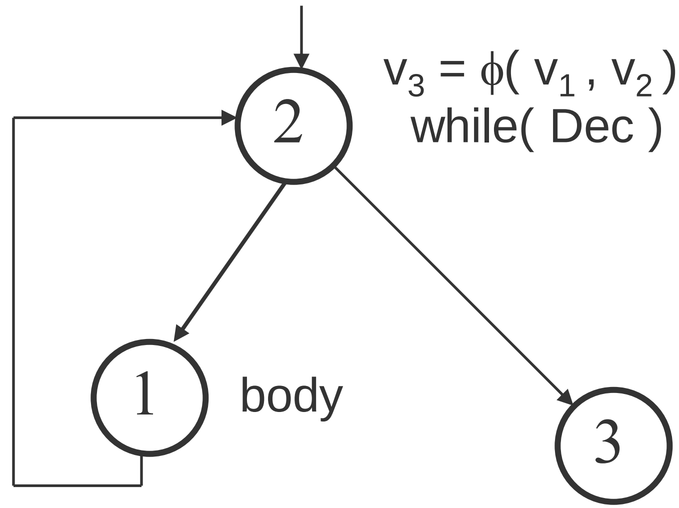
Conditional as global constraint: ite/6



$ite(\ x > 0,\ j_1,\ j_2,\ j_3,\quad j_1 = 5,\quad j_2 = 18\ )$ iff

- $x > 0 \quad \rightarrow \quad j_1 = 5 \ \wedge \ j_3 = j_1$
- $\neg(x > 0) \quad \rightarrow \quad j_2 = 18 \ \wedge j_3 = j_2$
- $\neg(\ x > 0 \ \wedge \ j_1 = 5 \ \wedge \ j_3 = j_1\ ) \ \rightarrow \ \neg(x > 0) \wedge \ j_2 = 18 \ \wedge j_3 = j_2$
- $\neg(\ \neg(x > 0) \wedge \ j_3 = j_2\ ) \ \rightarrow \ x > 0 \wedge \ j_1 = 5 \ \wedge j_3 = j_1$
- $\mathrm{Join}(\ x > 0 \wedge j_1 = 5 \wedge \ j_3 = j_1\ ,\quad \neg(x > 0) \wedge \ j_1 = 18 \wedge \ j_3 = j_2\ )$

Loop as global constraint: w/5



w(Dec, V_1, V_2, V_3, body) iff

- $Dec_{V3\leftarrow V1} \rightarrow body_{V3\leftarrow V1} \wedge \mathbf{w}(Dec, v_2, v_{new}, v_3, body_{V2\leftarrow Vnew})$
- $\neg Dec_{V3\leftarrow V1} \rightarrow v_3 = v_1$
- $\neg(Dec_{V3\leftarrow V1} \wedge body_{V3\leftarrow V1}) \rightarrow \neg Dec_{V3\leftarrow V1} \wedge v_3 = v_1$
- $\neg(\neg Dec_{V3\leftarrow V1} \wedge v_3 = v_1) \rightarrow Dec_{V3\leftarrow V1} \wedge body_{V3\leftarrow V1} \wedge \mathbf{w}(Dec, v_2, v_{new}, v_3, body_{V2\leftarrow Vnew})$
- $join(Dec_{V3\leftarrow V1} \wedge body_{V3\leftarrow V1} \wedge \mathbf{w}(Dec, v_2, v_{new}, v_3, body_{V2\leftarrow Vnew}),\ \neg Dec_{V3\leftarrow V1} \wedge v_3 = v_1)$

```
f(  int i  ) {
  j = 100;
  while( i > 1)
   { j++ ; i-- ;}
  ...
  if( j > 500)
    ...
```

w(Dec, V$_1$, V$_2$, V$_3$, body) :-

- $Dec_{V3\leftarrow V1} \rightarrow body_{V3\leftarrow V1} \wedge \mathbf{w}(Dec, v_2, v_{new}, v_3, body_{V2\leftarrow Vnew})$
- $\neg Dec_{V3\leftarrow V1} \rightarrow v_3=v_1$
- $\neg(Dec_{V3\leftarrow V1} \wedge body_{V3\leftarrow V1}) \rightarrow \neg Dec_{V3\leftarrow V1} \wedge v_3=v_1$
- $\neg(\neg Dec_{V3\leftarrow V1} \wedge v_3=v_1) \rightarrow$
  $Dec_{V3\leftarrow V1} \wedge body_{V3\leftarrow V1} \wedge \mathbf{w}(Dec,v_2,v_{new},v_3,body_{V2\leftarrow Vnew})$
- $join(Dec_{V3\leftarrow V1} \wedge body_{V3\leftarrow V1} \wedge \mathbf{w}(Dec,v_2,v_{new},v_3,body_{V2\leftarrow Vnew}$,
  $\neg Dec_{V3\leftarrow V1} \wedge v_3=v_1)$

$i = 23,\ j_1=100$?

no

i in $401..2^{31}-1$

$$\boxed{\mathbf{w(i_3 > 1, (i,j_1), (i_2,j_2), (i_3,j_3),\ \ j_2 = j_3 + 1 \wedge i_2 = i_3 - 1)}}$$

$i_3 = 1,\ j_3 = 122$

$i_3 = 10$?

$j_1 = 100$,

$j_3 > 500$?

Features of the w relation

- ✓ It can be nested into other relations ite/6 or w/5
  (e.g., nested loops w($cond_1$, v_1,v_2,v_3, w($cond_2$, ...))

- ✓ Managed by the solver as any other constraint (its consistency is iteratively checked, awakening conditions, success/failure/suspension)

- ✓ By construction, w is unfolded only when necessary but
  w may NOT terminate !

- ✓ Join is implemented using Abstract Interpretation operators (interval union, weak-join, widening)

(Gotlieb et al. CL'2000) (Denmat Gotlieb Ducassé ISSRE'07)
(Denmat Gotlieb Ducassé CP'2007)

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Constraint-based exploration

Summary and further work

CBT (summary)

Proved concept in code-based automatic test data generation

Two main approaches:
- Path-oriented exploration (using symbolic evaluation techniques)
- Constraint-based exploration (using global constraints)

Constraint solving:
- Linear programming
- SMT-solvers
- Constraint Programming techniques with *abstraction-based relaxations*

Mature tools (academic and industrial) exist, but problems remain for handling efficiently complex code (pointer arithmetic, transtyping, etc.), non-feasible code leading to unsatisfiable constraint systems, large data structures…

Further work

- Constraint acquisition for learning preconditions and generating satisfying test inputs (PhD G. Menguy, joint work with CEA, France)
- Initial states generation for testing optimal AI planners
- Test case execution scheduling with constraint acquisition

We are a team of researchers interested by real-world applications that lead to applied research problems. Long-term experience in technology transfer and technology adoption.