

An Improved Distance Heuristic Function for Directed Software Model Checking

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Motivation

- ◆ Use of embedded systems has become ubiquitous
- ◆ Growing complexity challenges ad-hoc testing methods
- ◆ Vector simulation finds bugs in the early design phase
- ◆ Code coverage techniques are not feasible
- ◆ Low-level scheduling decisions create concurrency errors
- ◆ Motivates a need for a formal approach to find these errors



Software Model Checking

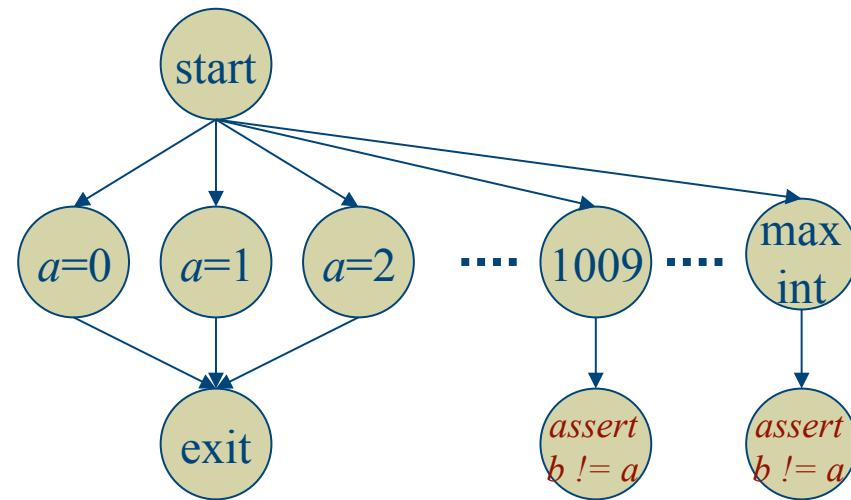
```
int b = 1009
void simple(){
    int a;
    read a;
    if (a > 1000)
        assert(b != a)
}
```

- ♦ It builds a model for a given software system



Simple program

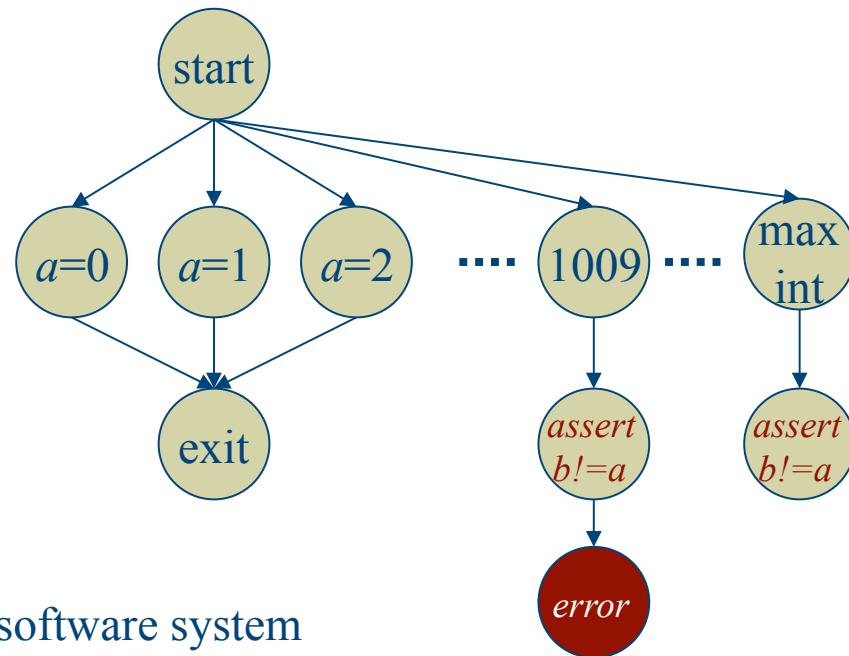
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int b = 1009
void simple0{
    int a;
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- ◆ It builds a model for a given software system
- ◆ The transition graph represents all the behaviors of the system

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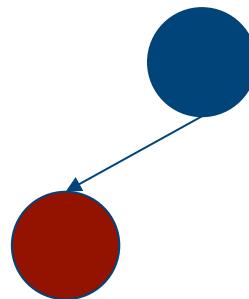


- ◆ It builds a model for a given software system
- ◆ The transition graph represents all the behaviors of the system
- ◆ The property being verified is whether there exists a path to the error

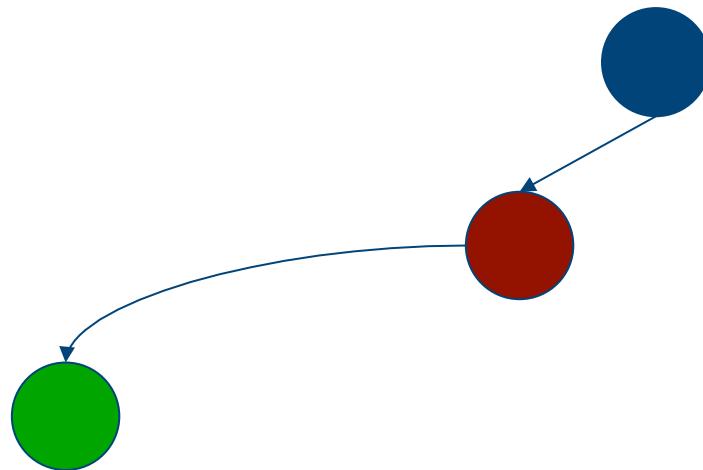
Exhaustive Search - DFS



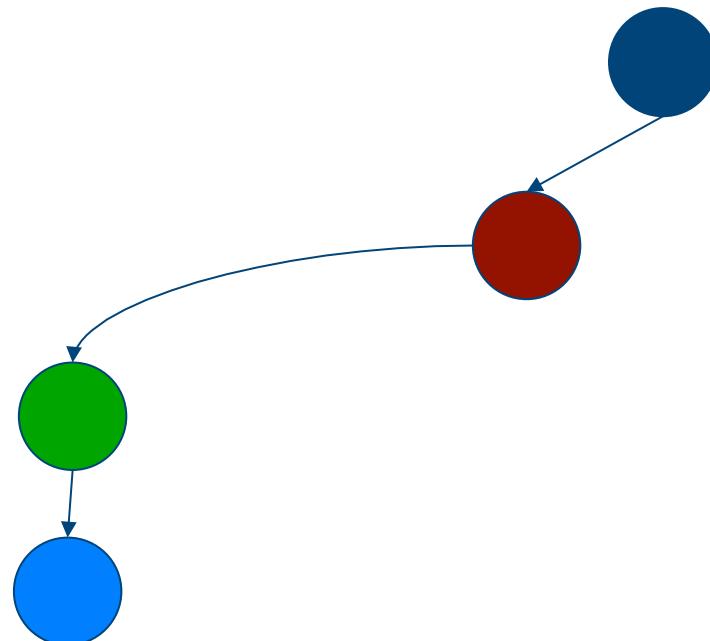
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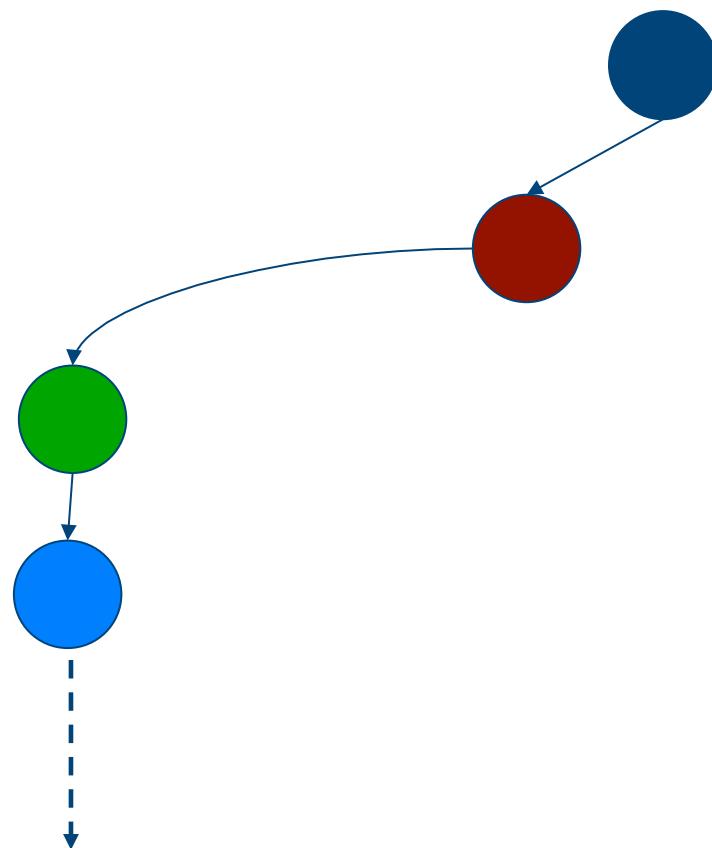
Exhaustive Search - DFS



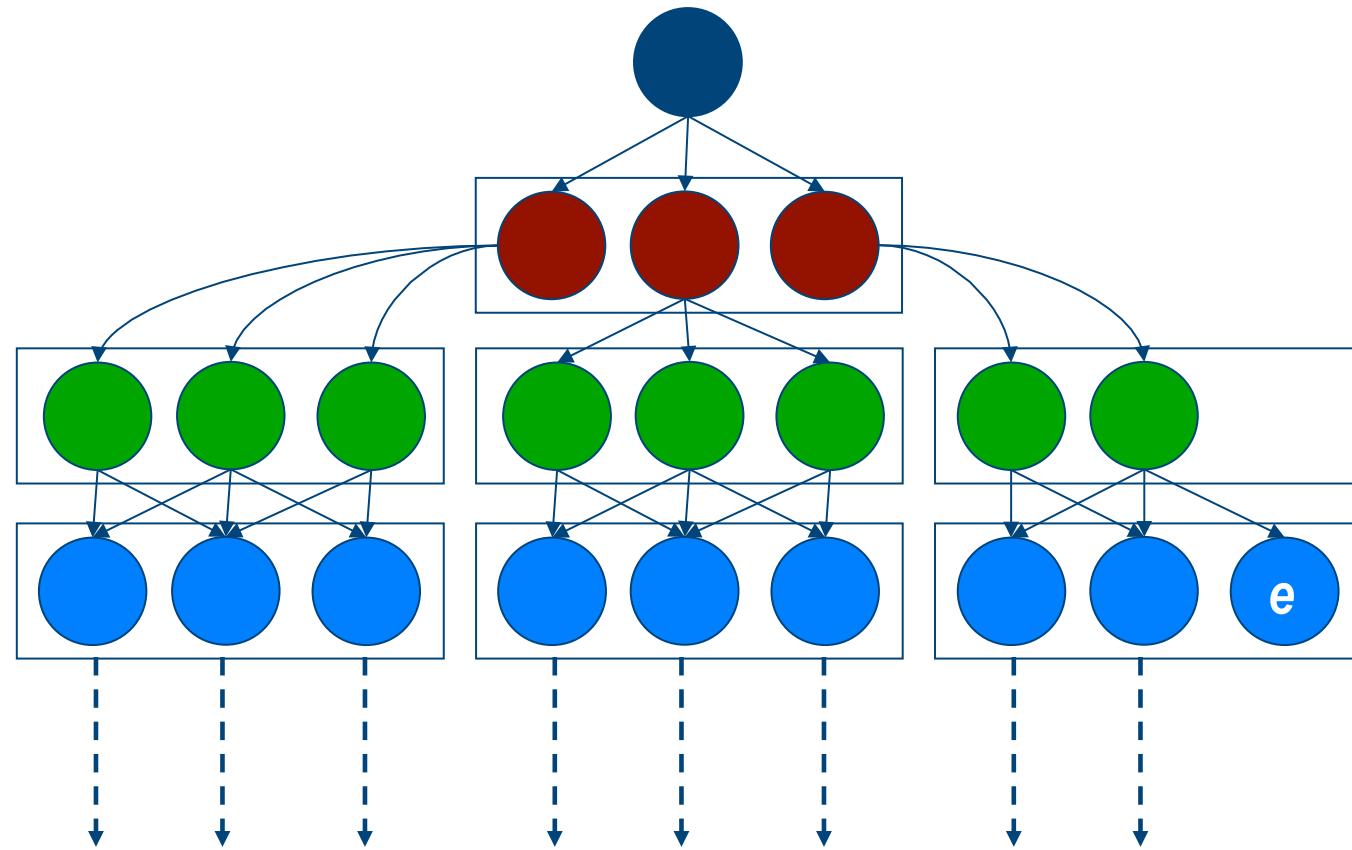
Exhaustive Search - DFS



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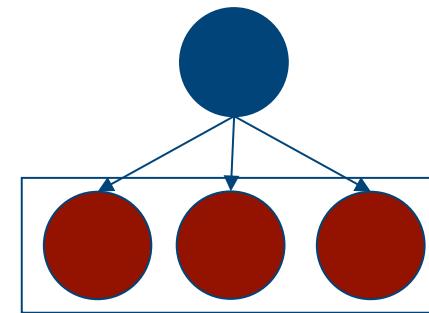
Exhaustive Search - DFS



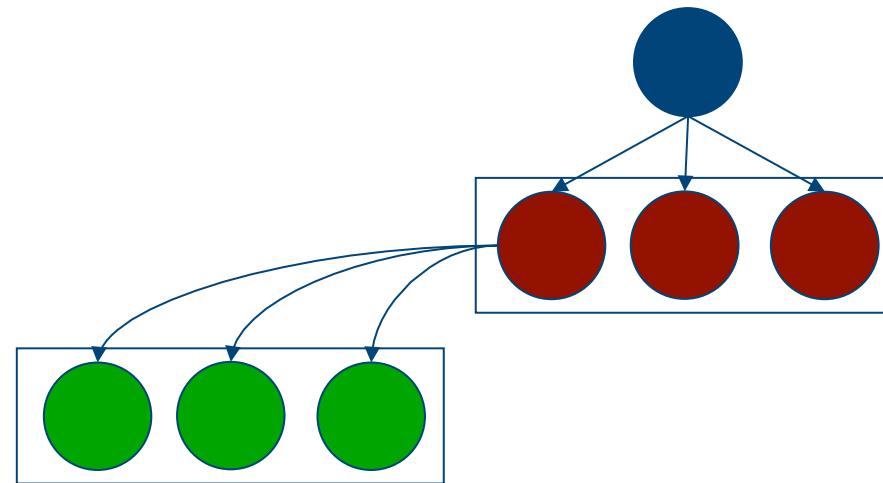
Exhaustive Search - BFS



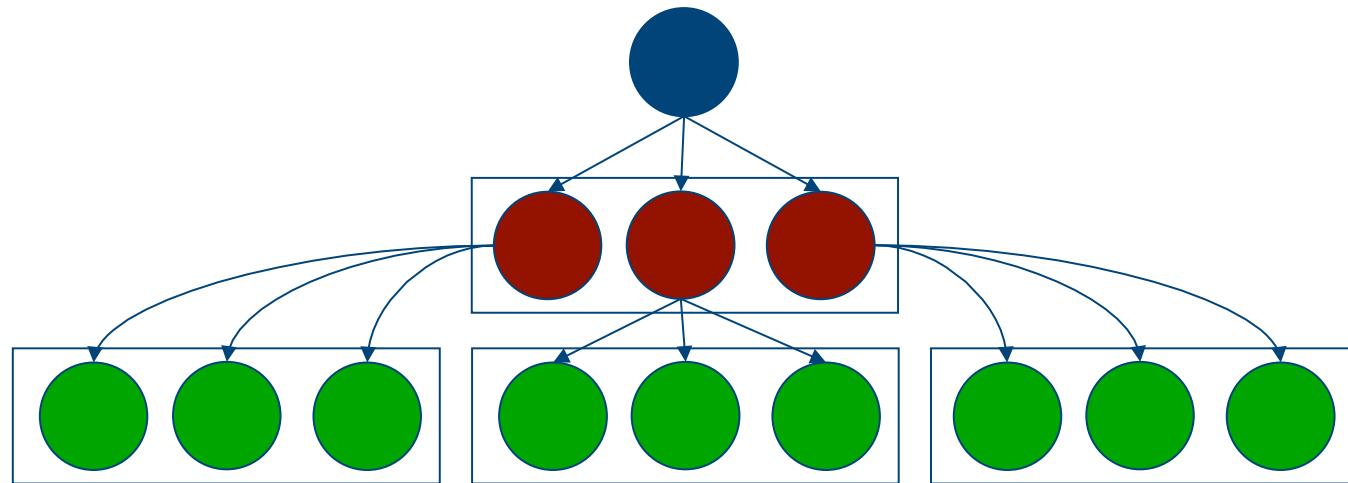
Exhaustive Search - BFS



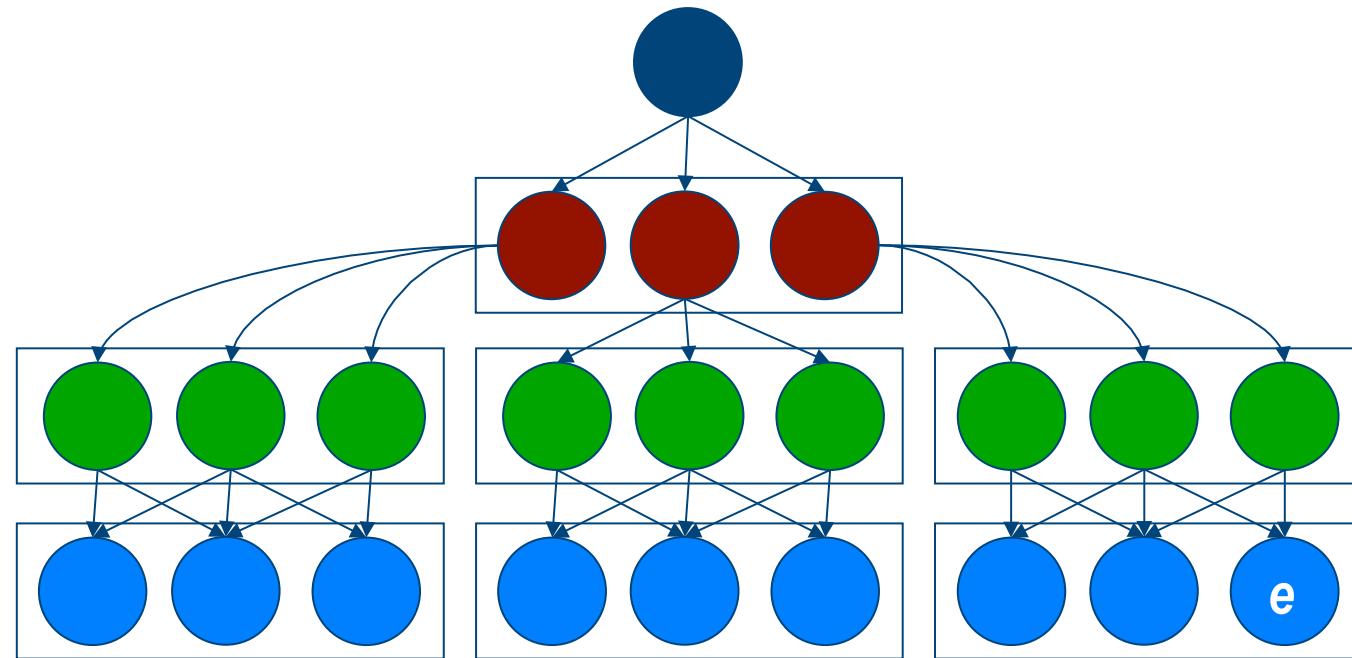
Exhaustive Search - BFS



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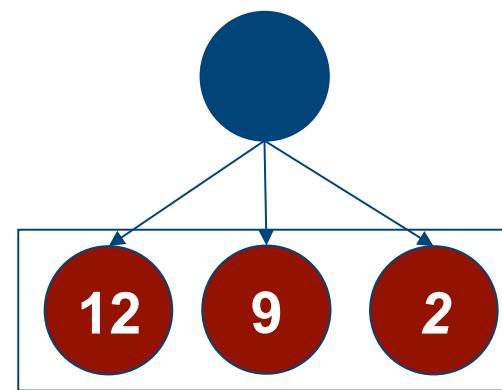
Exhaustive Search - BFS



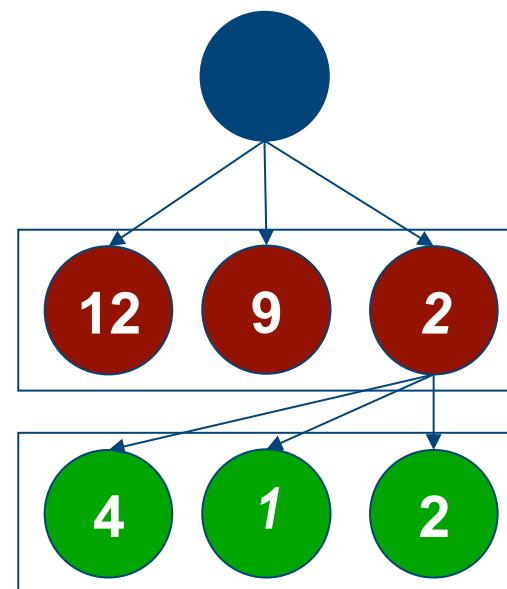
Guided Best-first Search



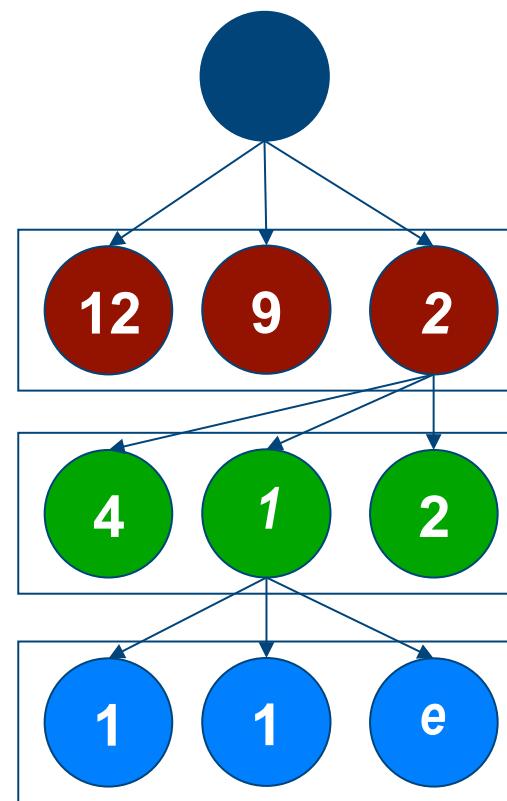
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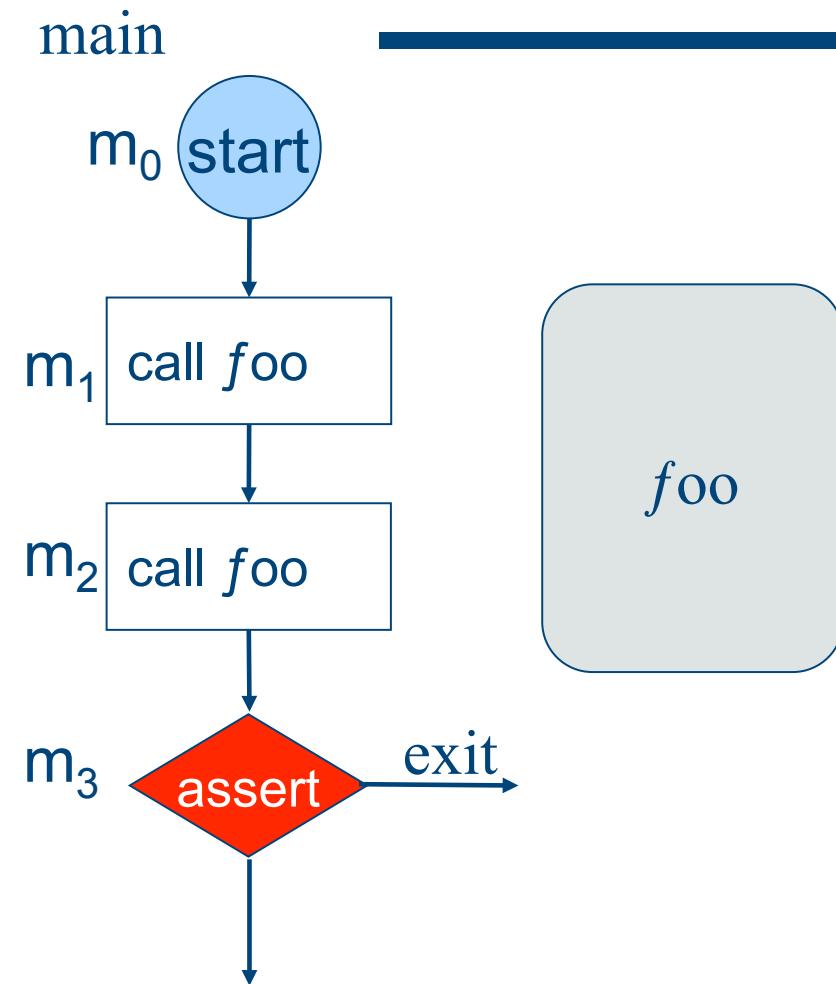


Related Work on Heuristic estimates

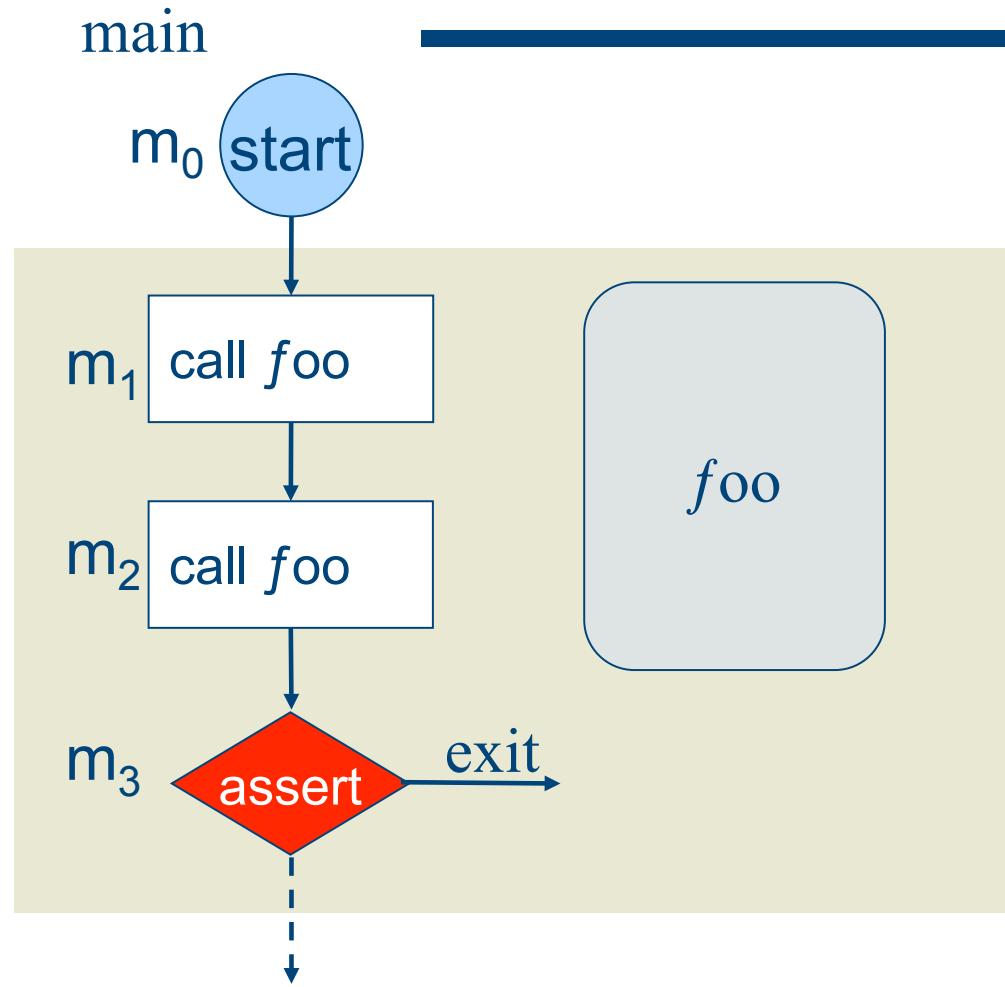
- ◆ *Edelkamp, Lafuente, and Leue*
- ◆ Minimum number of changes in program values
- ◆ *Seppi, Jones, and Lamborn*
- ◆ Use Bayesian reasoning
- ◆ *Visser and Groce*
- ◆ Structural properties of thread interdependencies
- ◆ *Edelkamp and Mehler*
- ◆ Minimal number of transitions (FSM distance)
- ◆ *Rungta and Mercer*
- ◆ Use partial context information to improve FSM distance



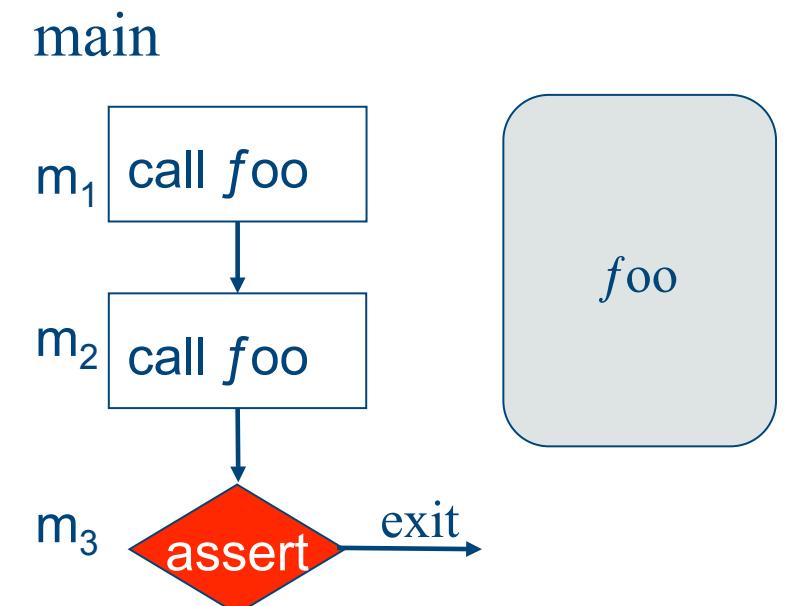
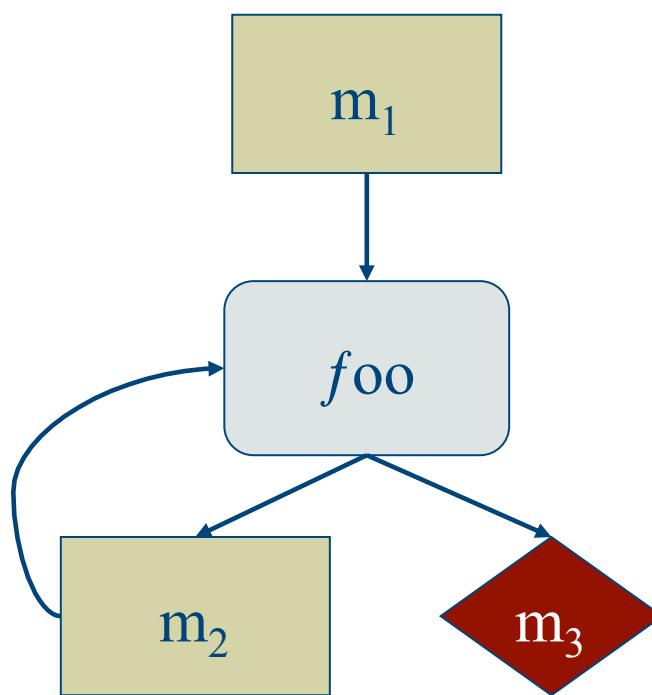
FSM Distance Heuristic



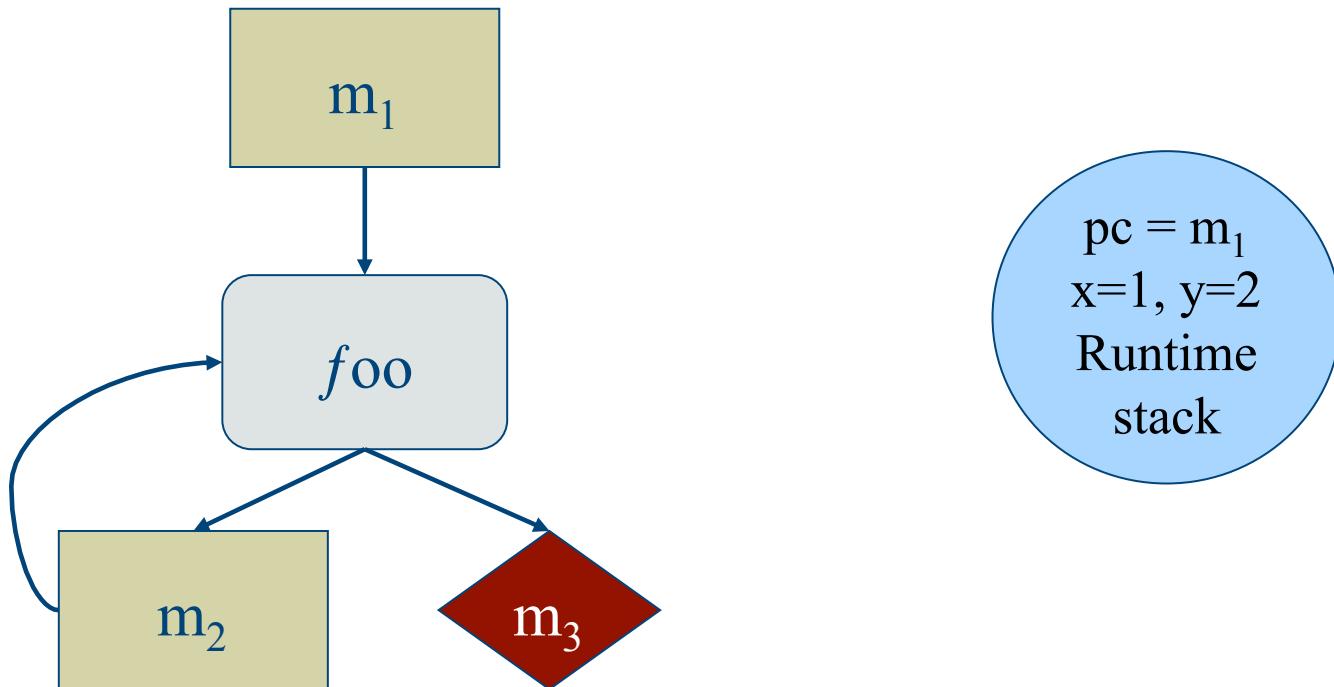
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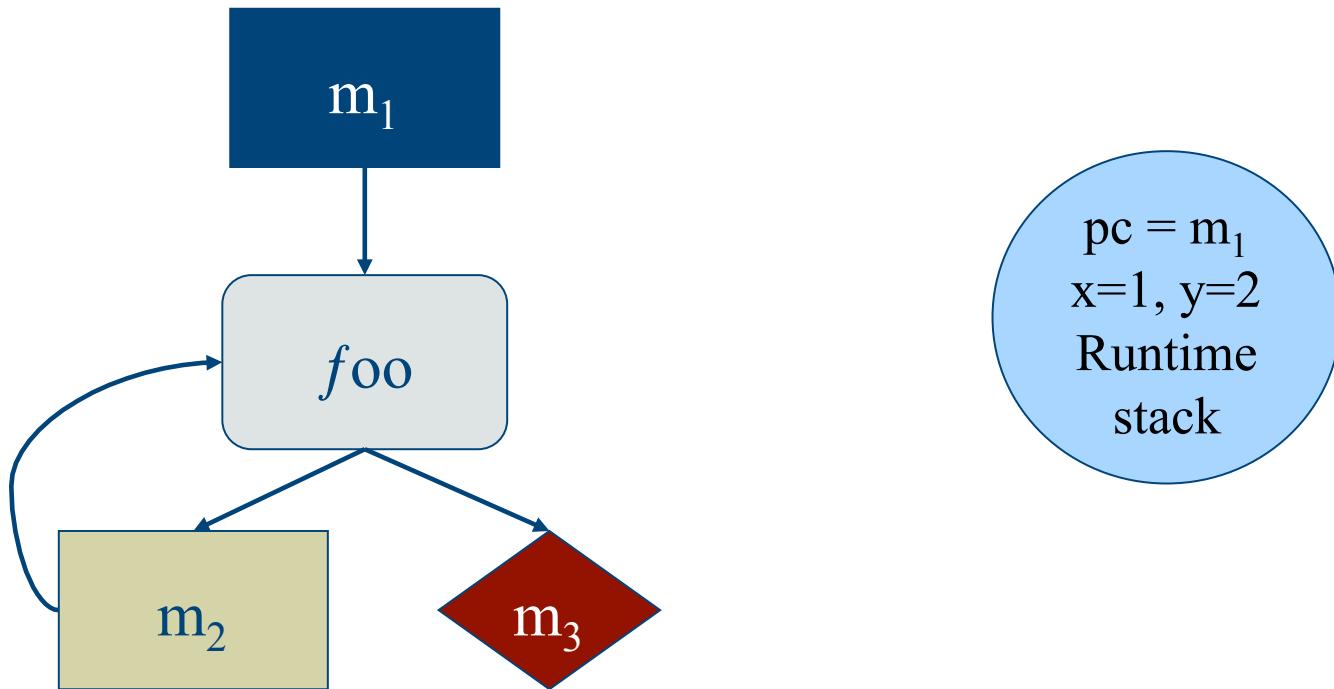
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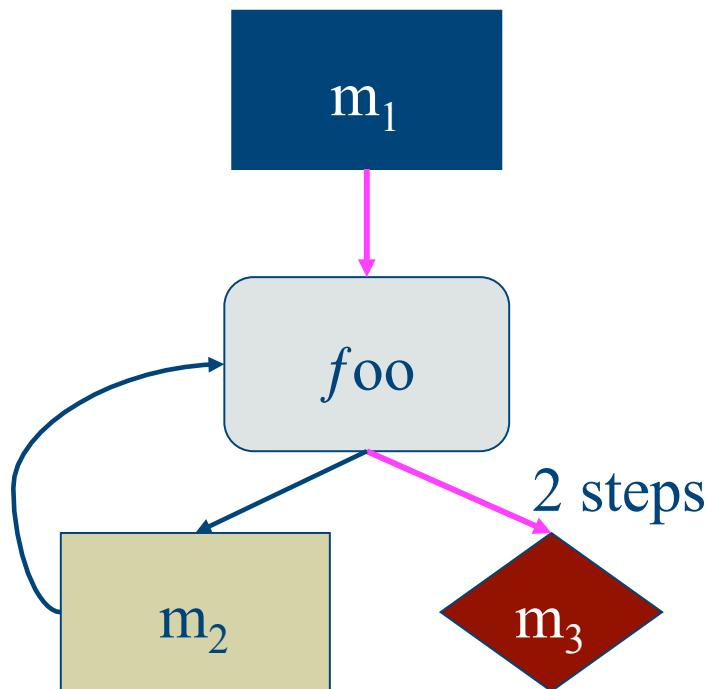
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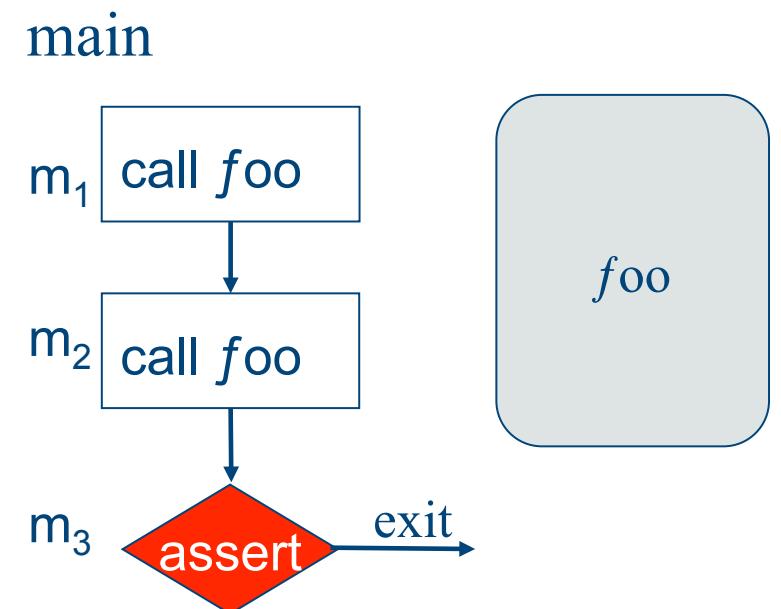
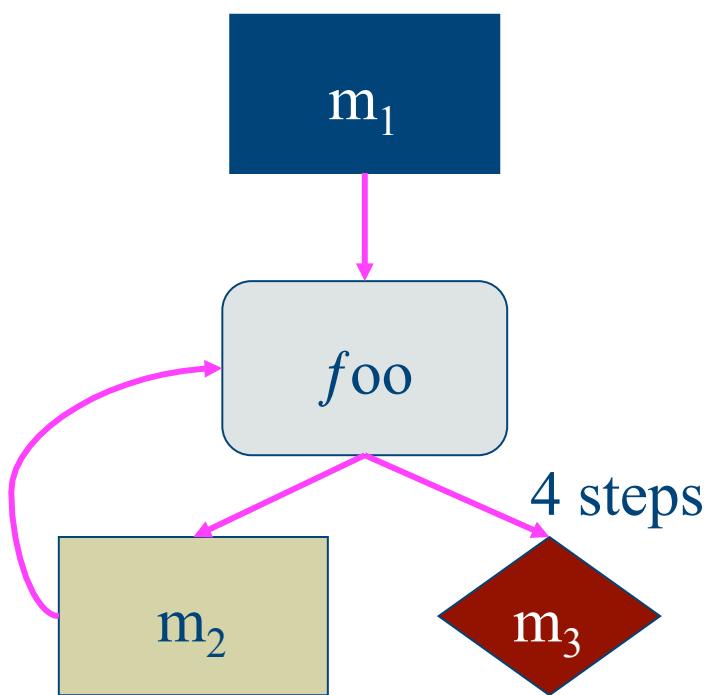


FSM Distance Heuristic

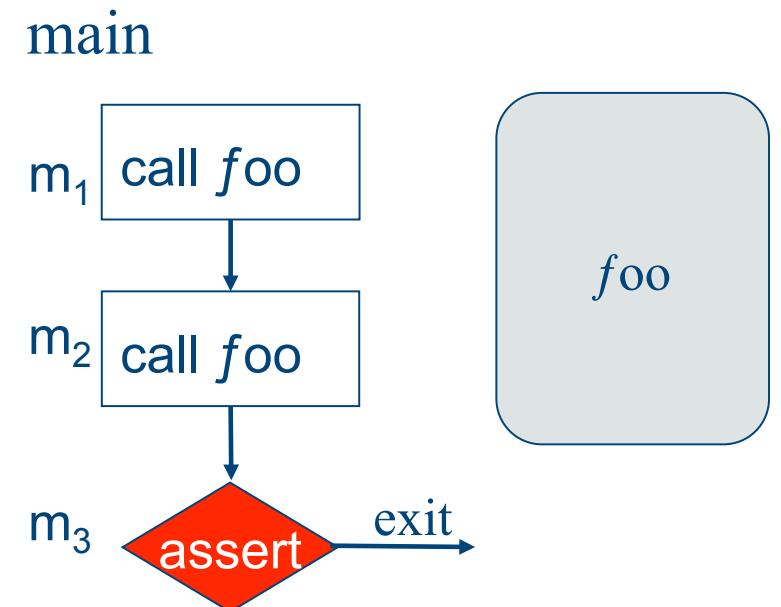
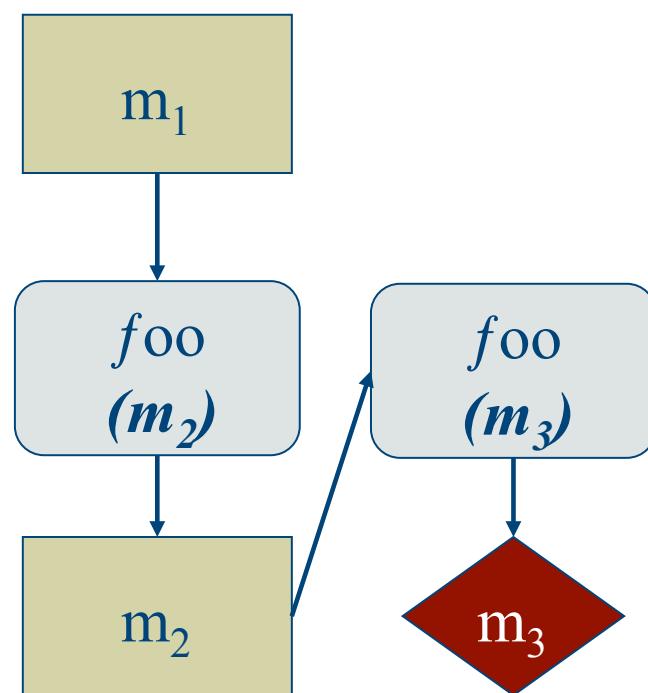


pc = m_1
 $x=1, y=2$
Runtime
stack

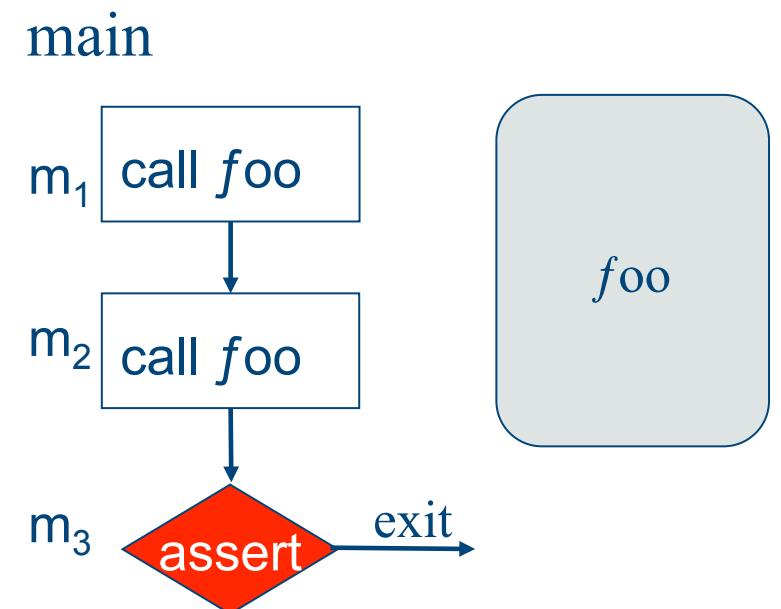
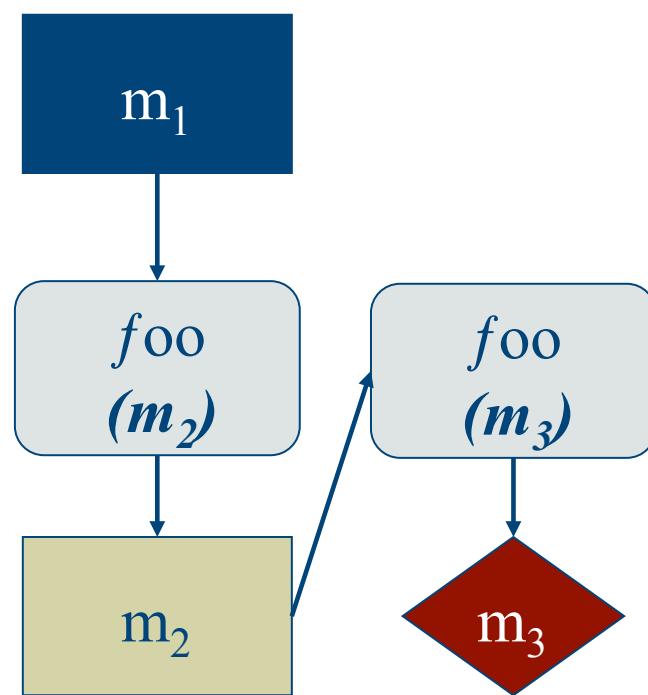
Lack of Context



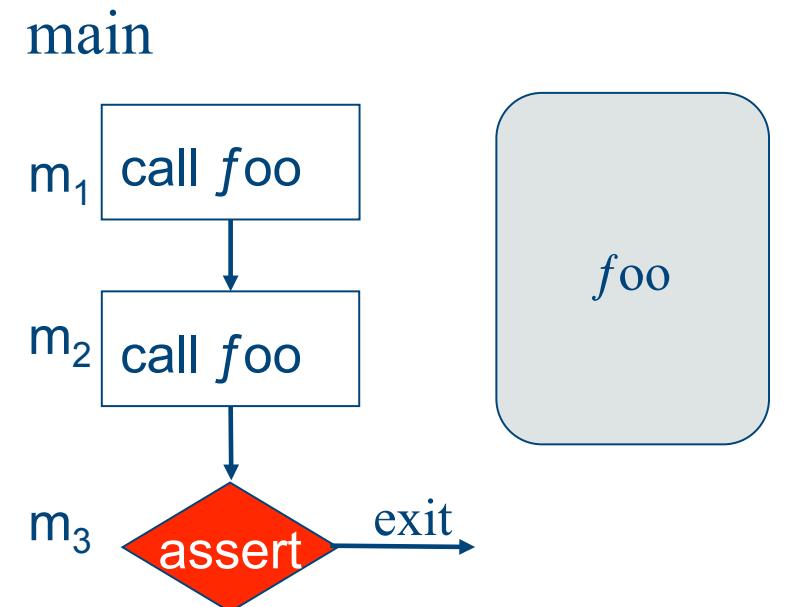
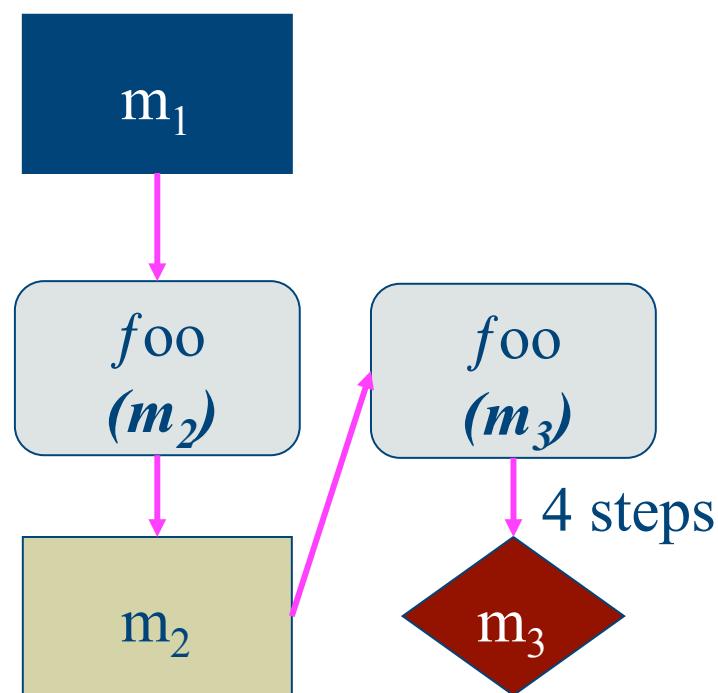
k-bounded Graph



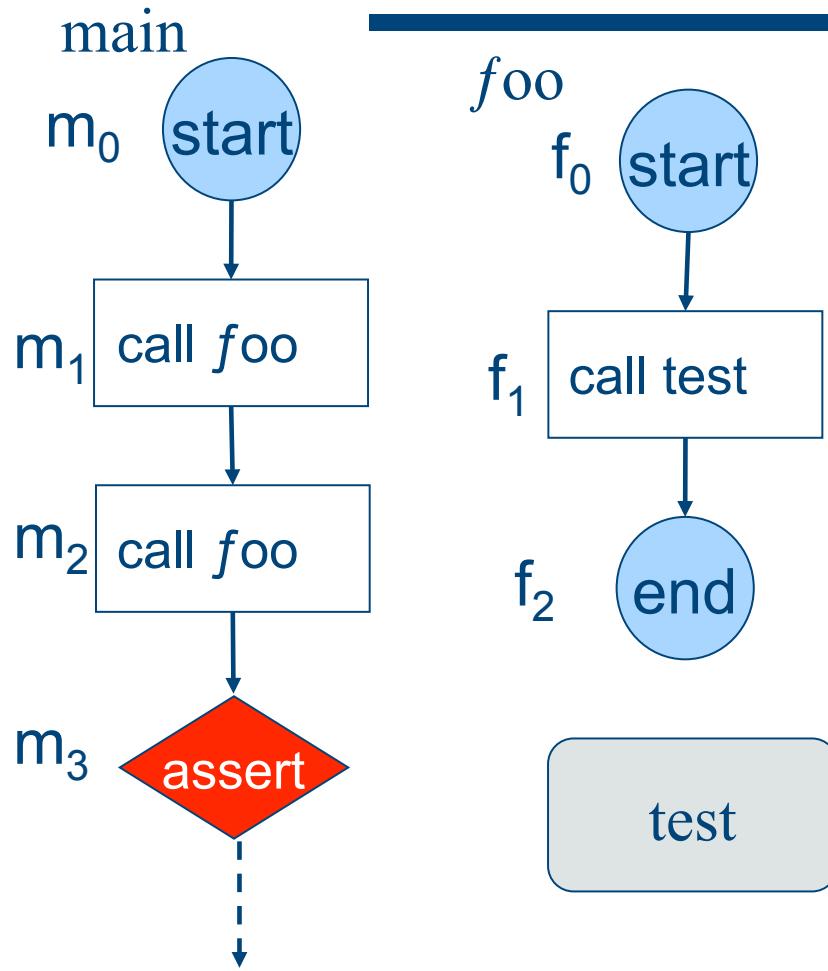
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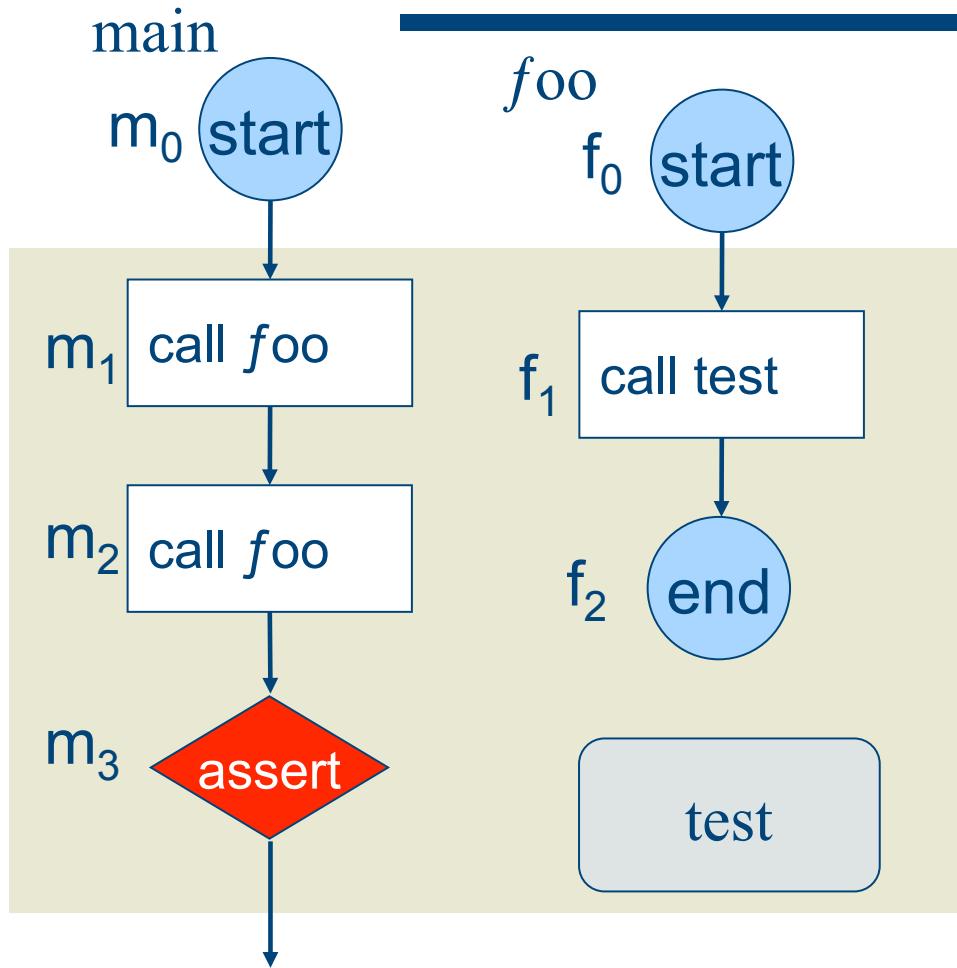
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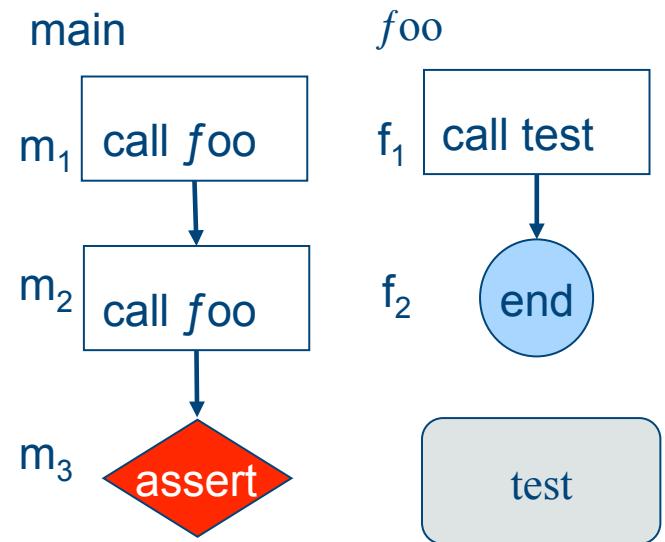
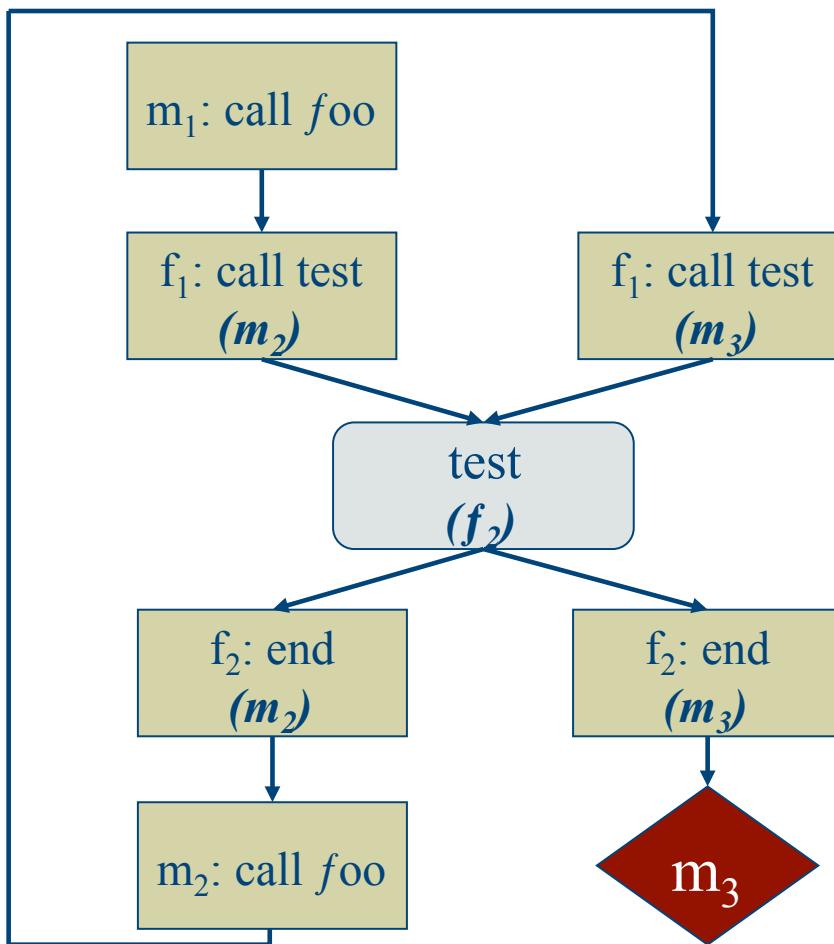
EFSM Distance Heuristic



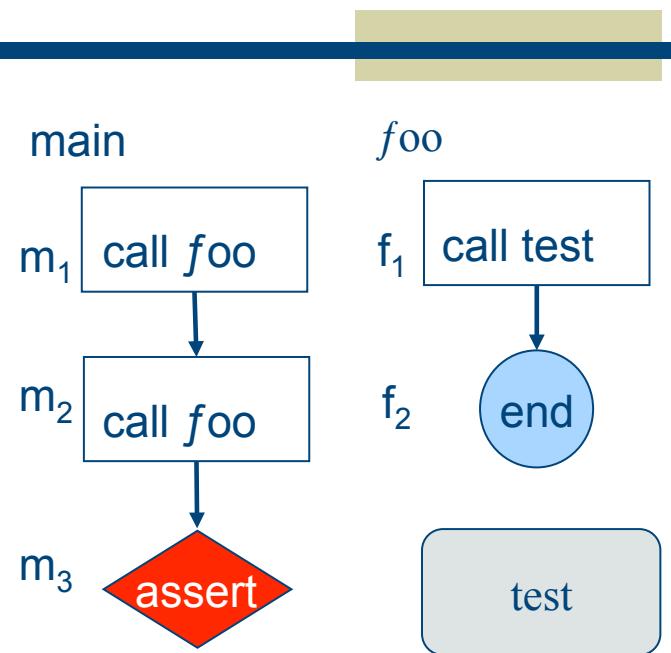
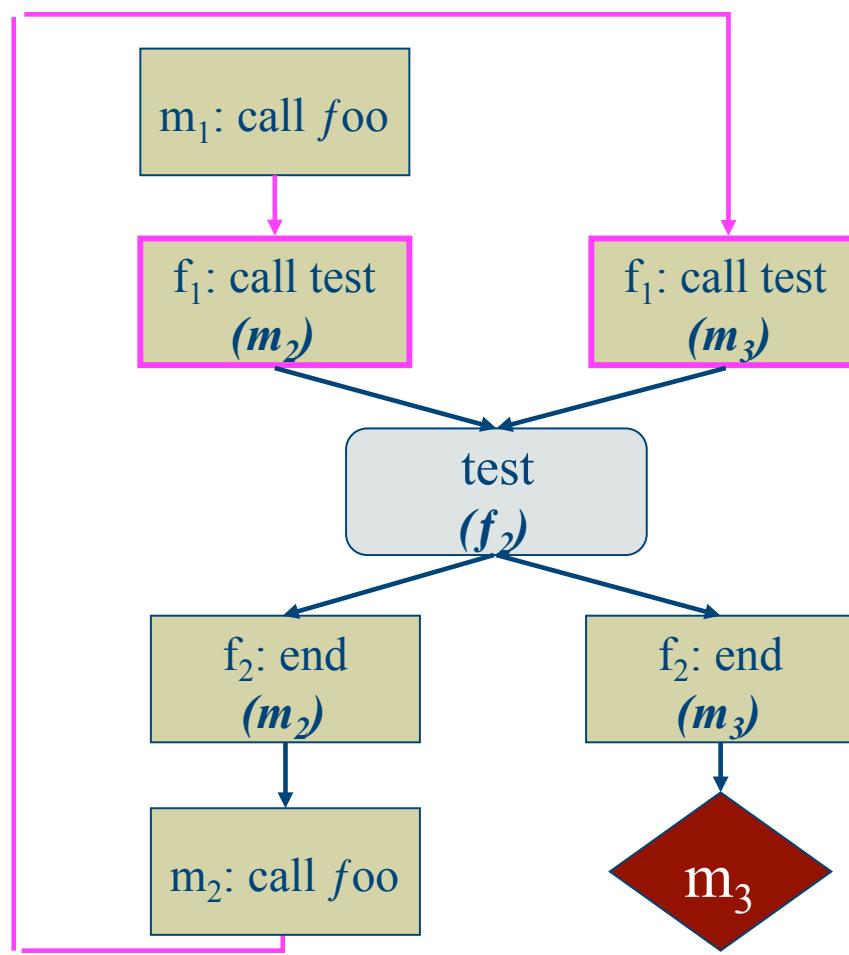
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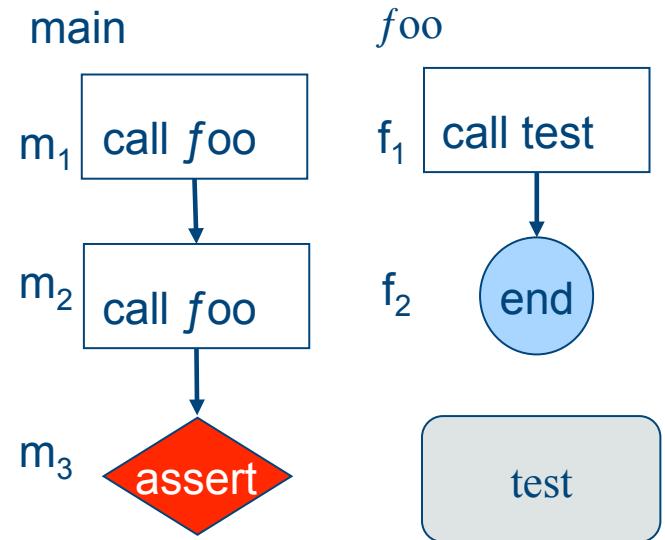
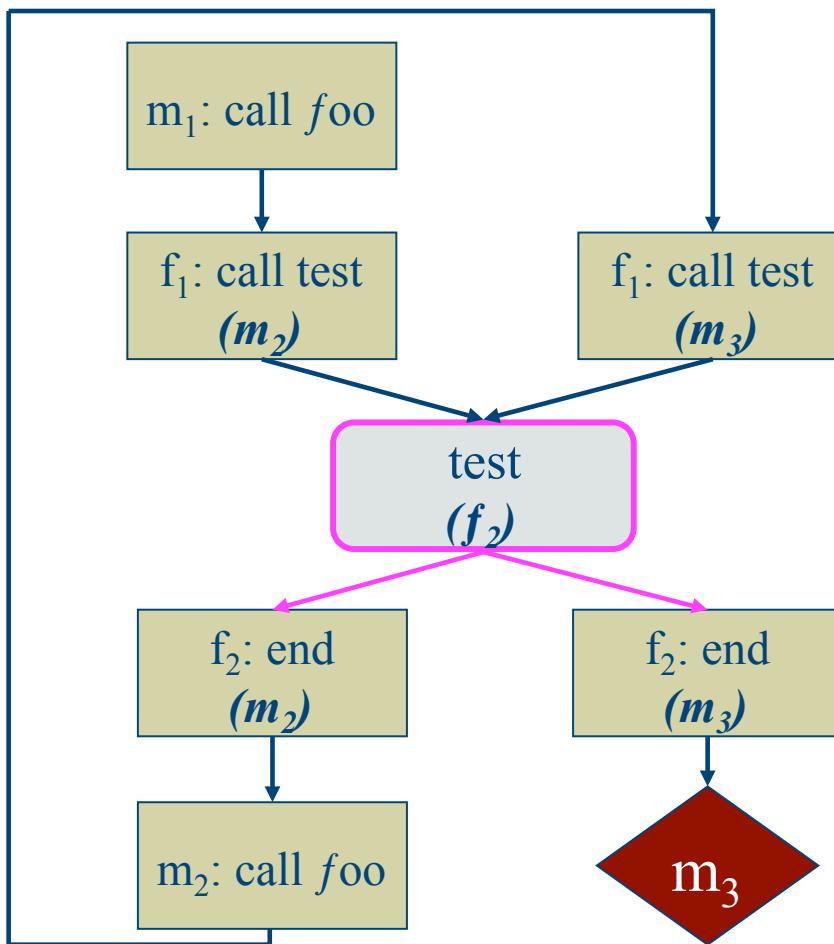
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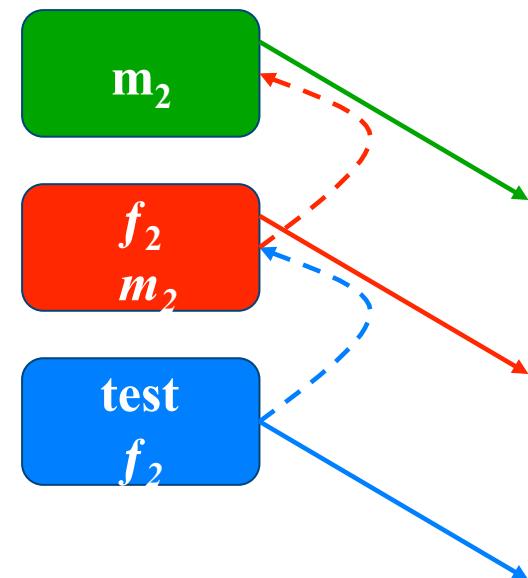
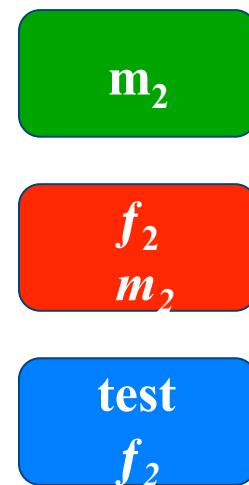
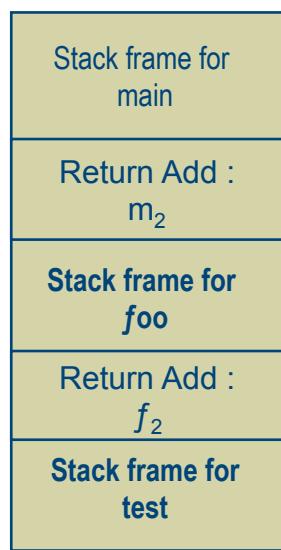
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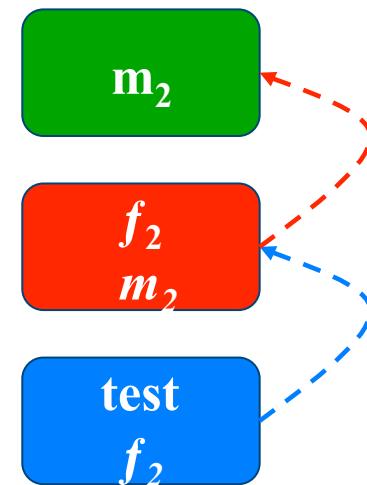
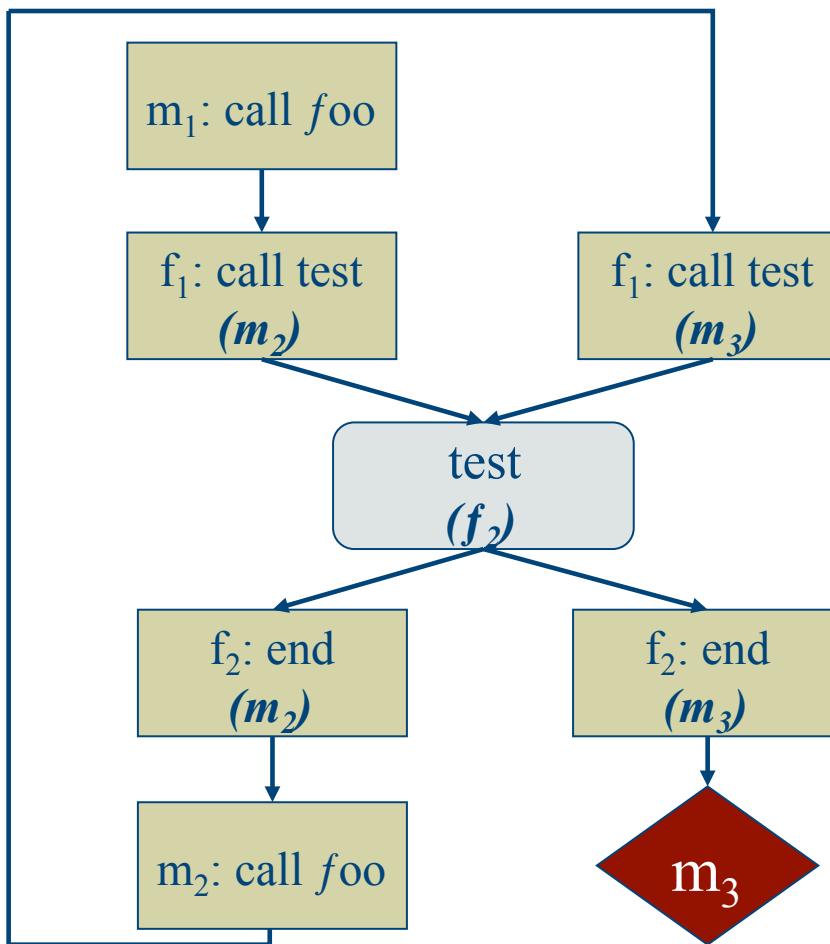
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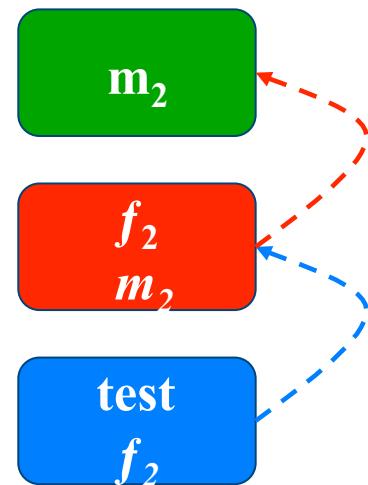
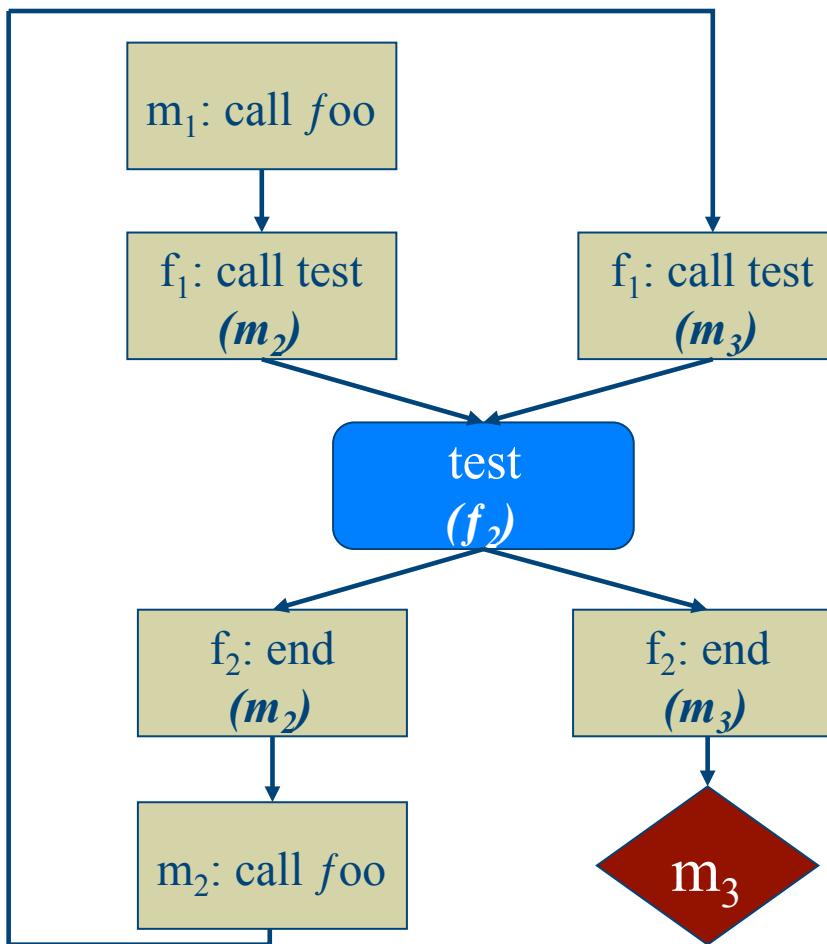
Recreate the call trace



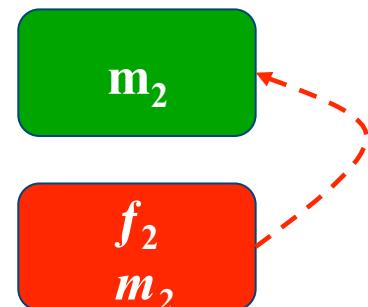
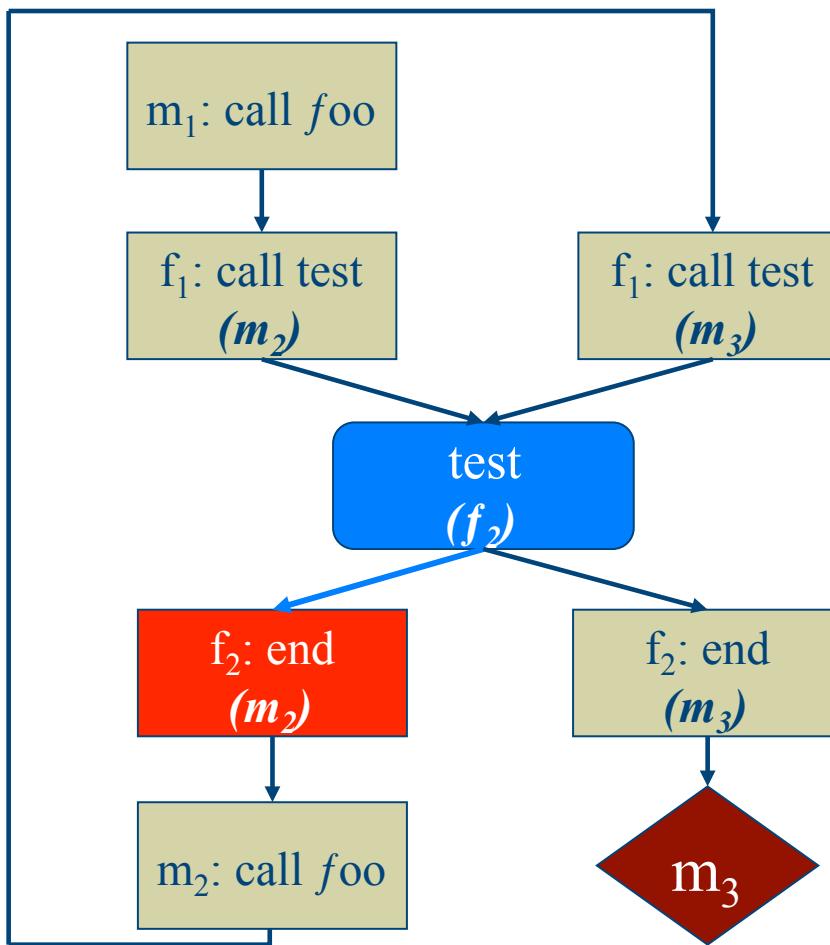
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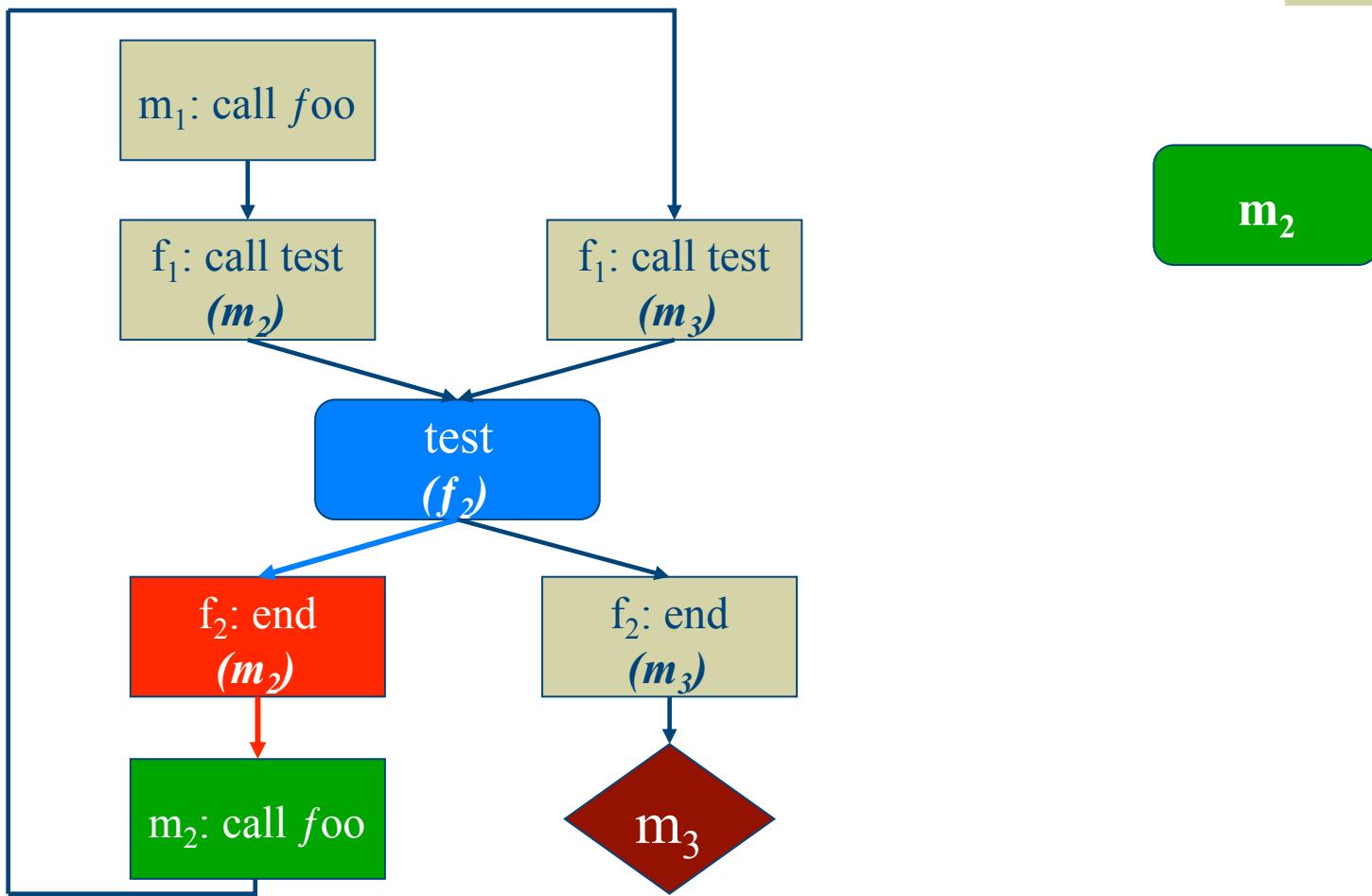
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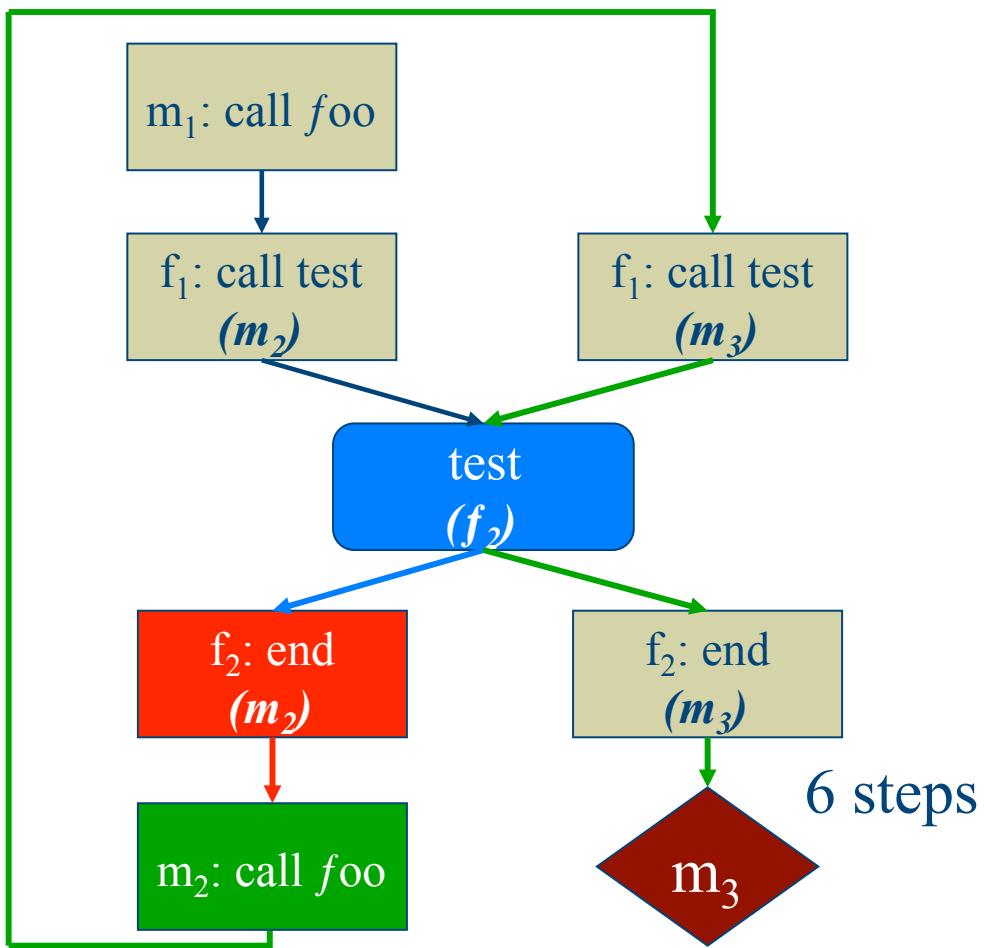
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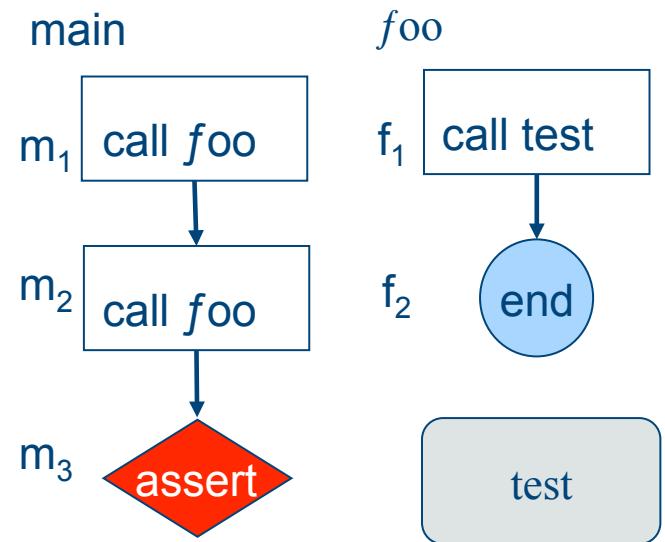
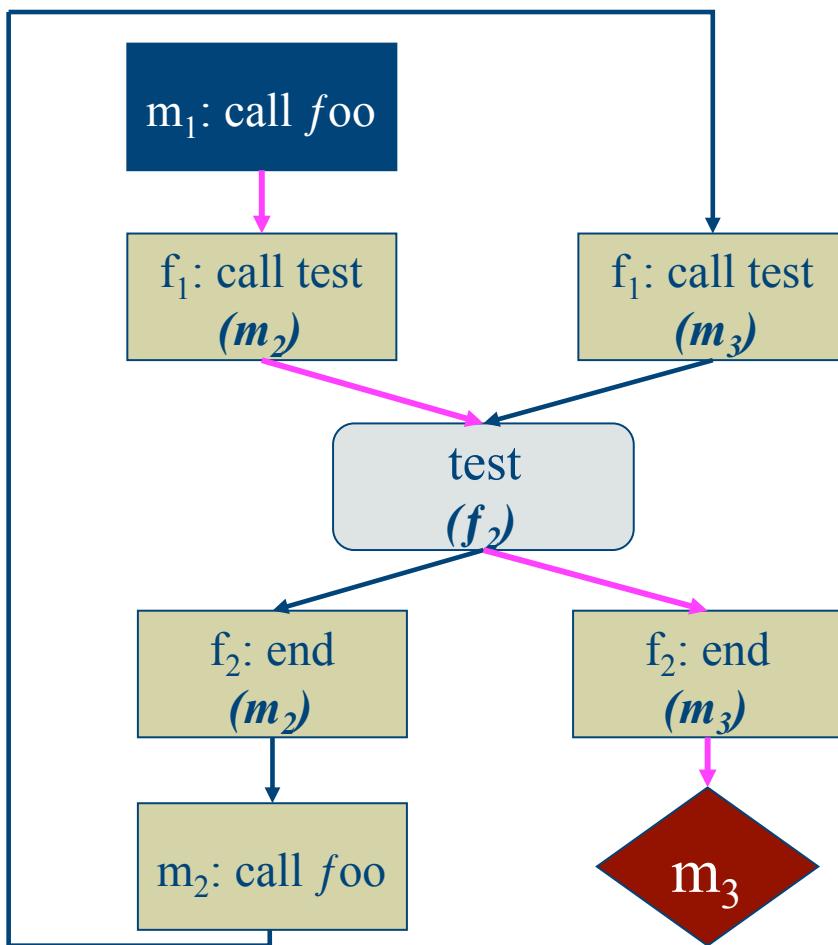
EFSM Distance Heuristic



EFSM Distance Heuristic the Heuristic



Forward estimates are inaccurate

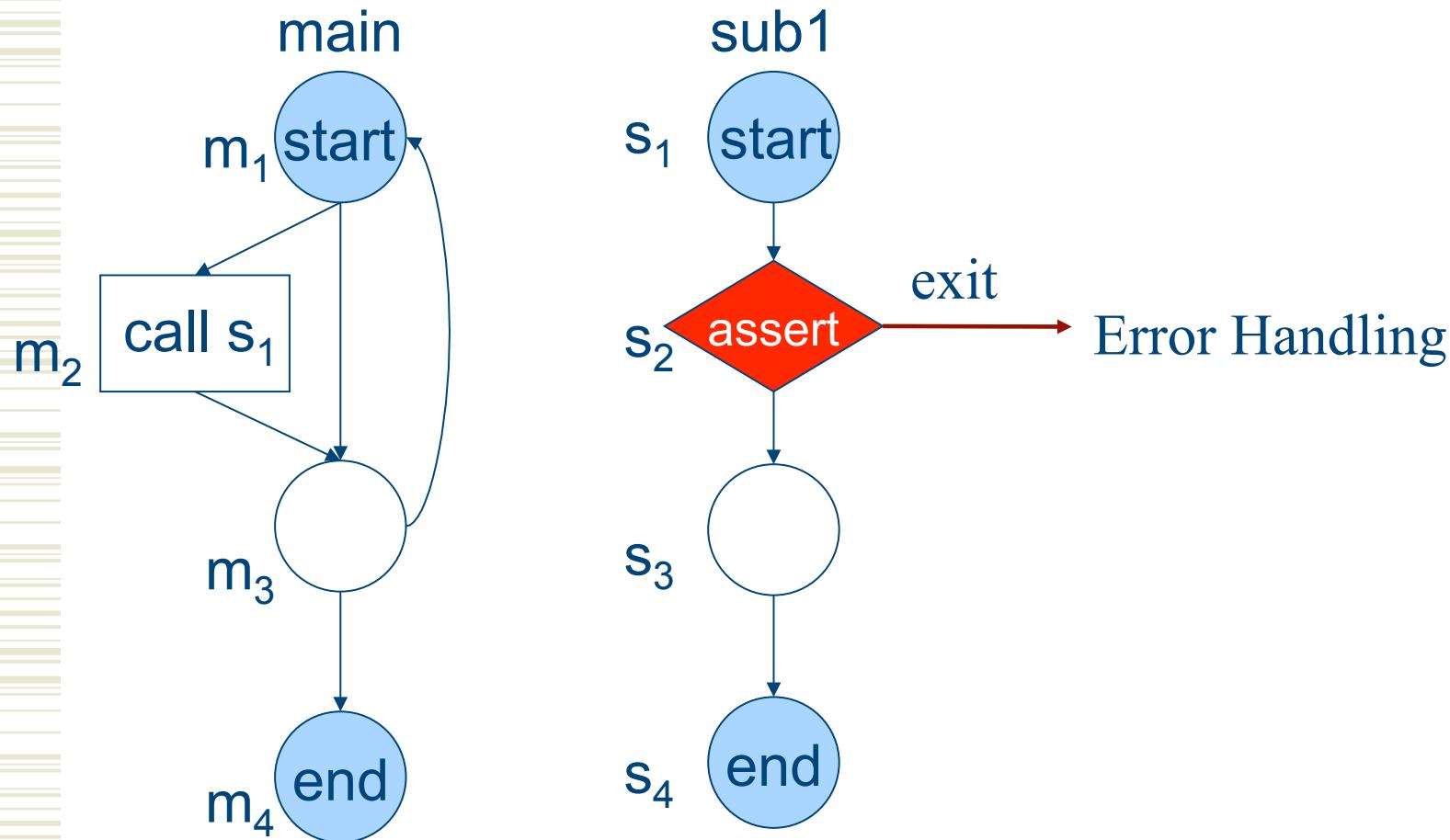


Full Context Aware (FCA)

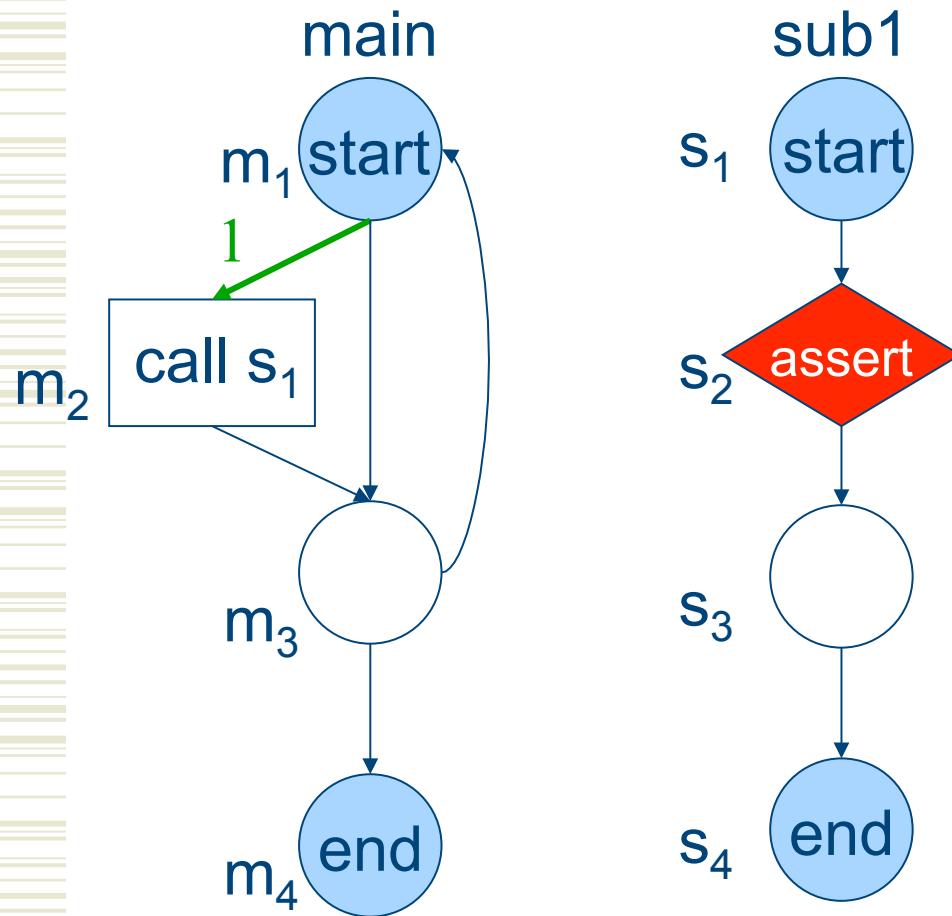
- ◆ Assume no recursion and resolved call-sites
- ◆ Statically compute distance estimates
- ◆ Full context information in the forward direction



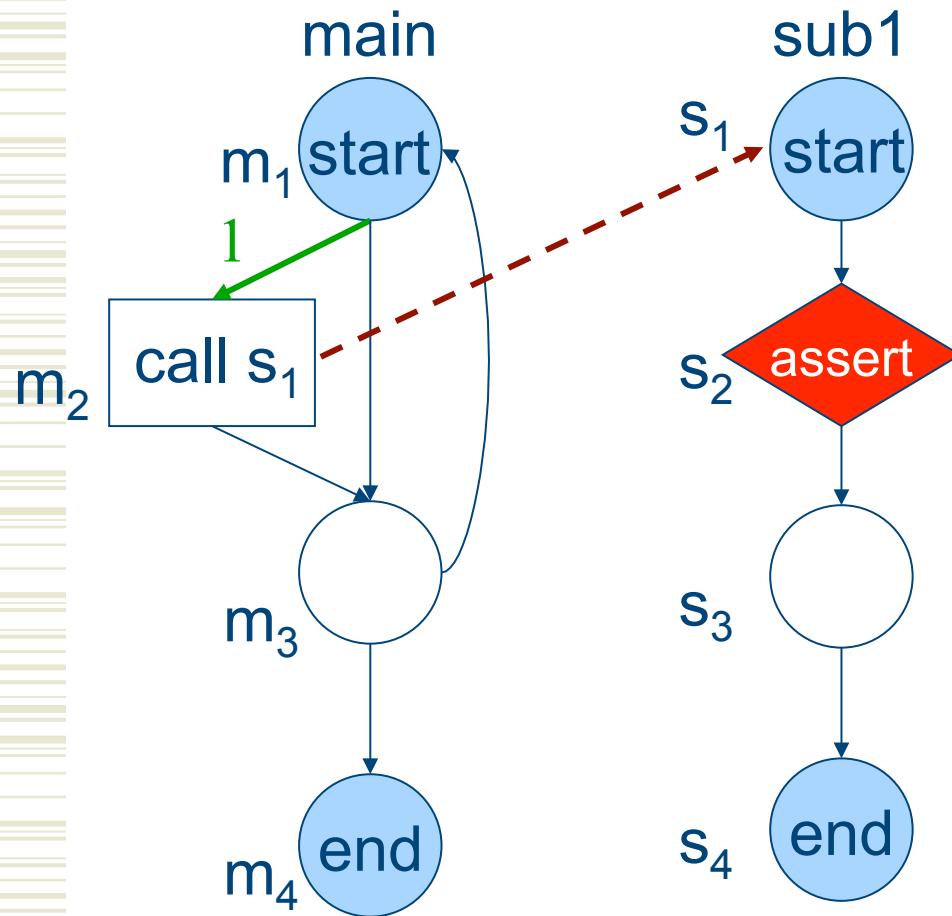
Full Context Example



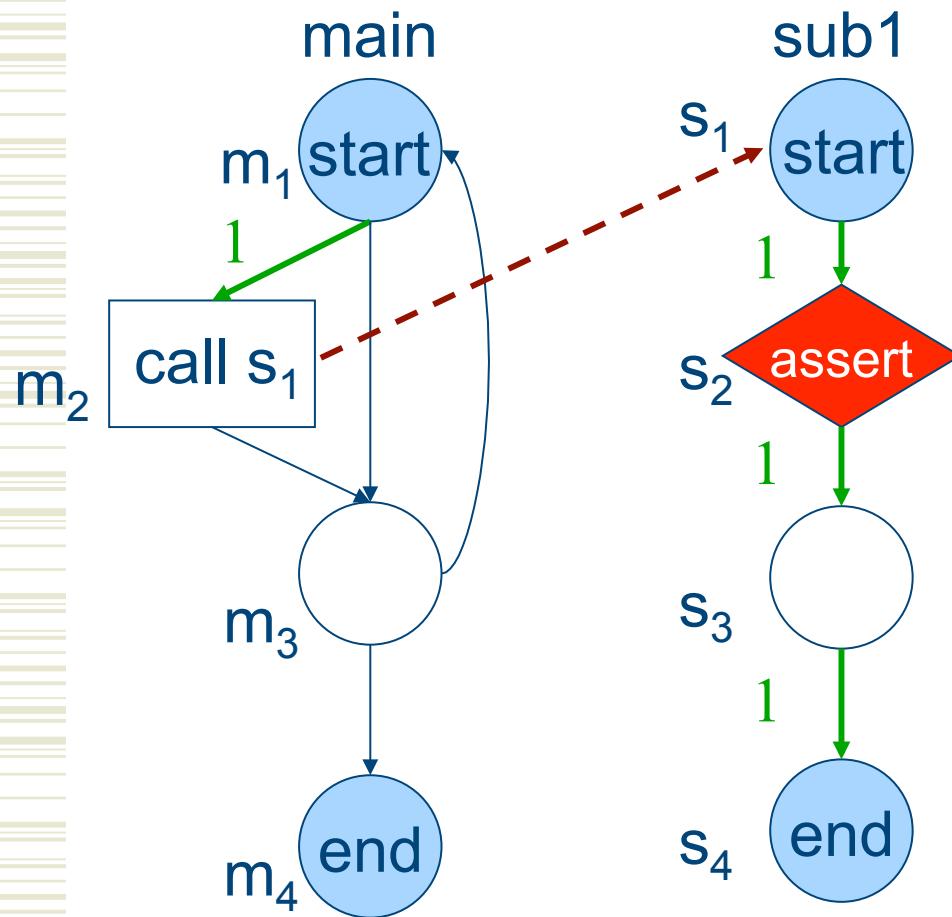
Start DFS at Main CFG



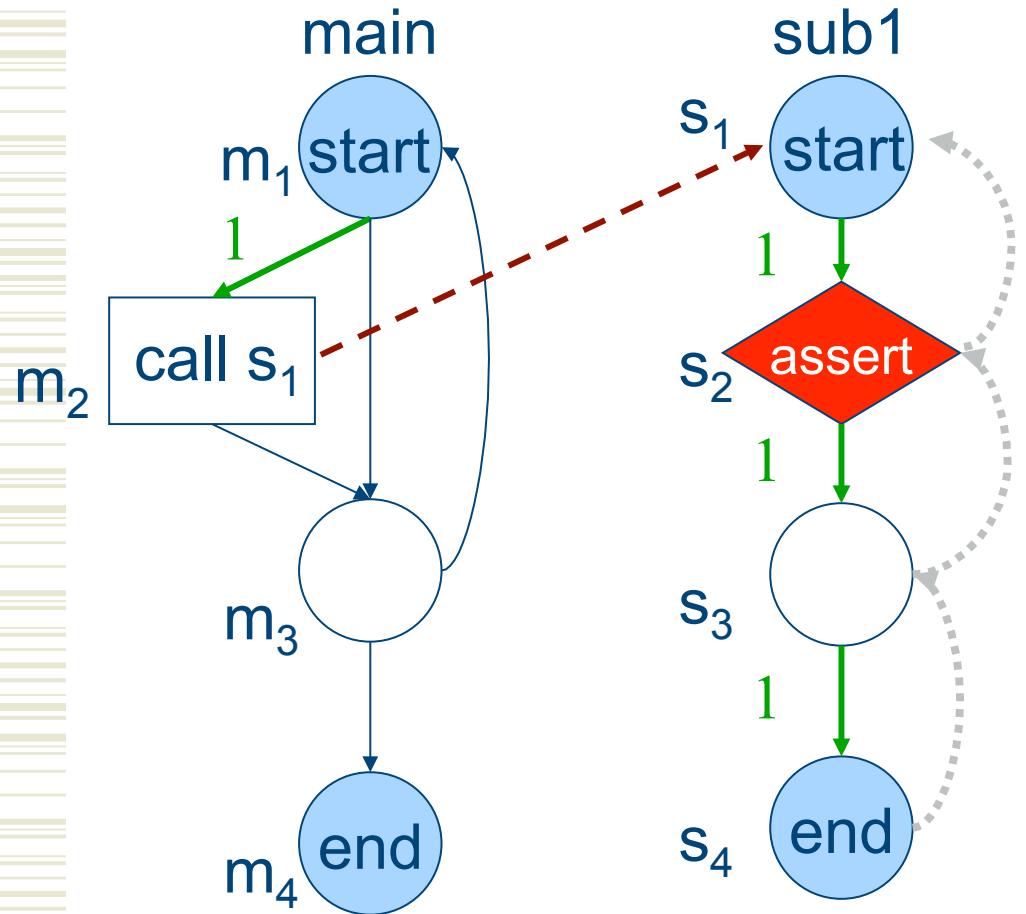
At Call node move to Target



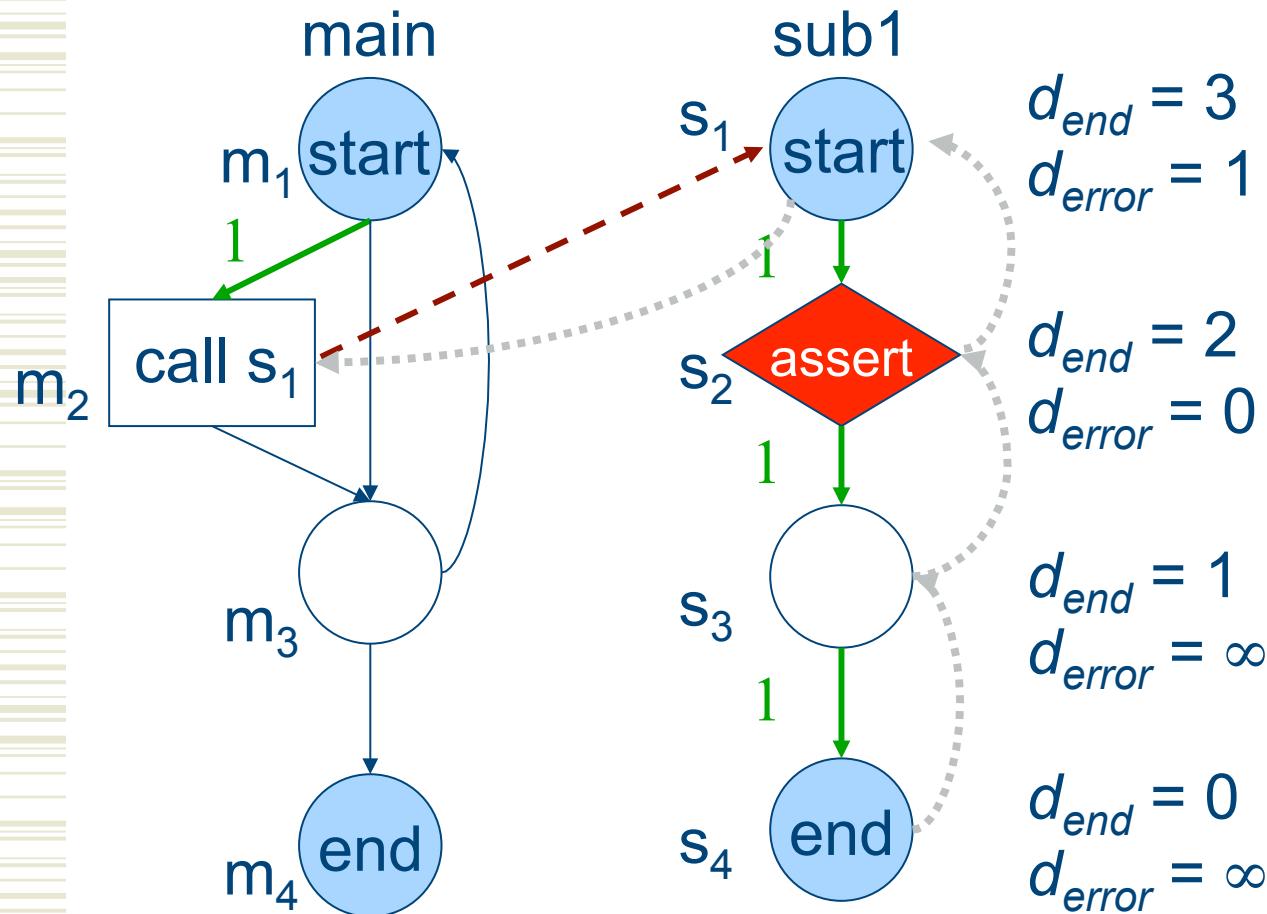
Note the edge costs of nodes



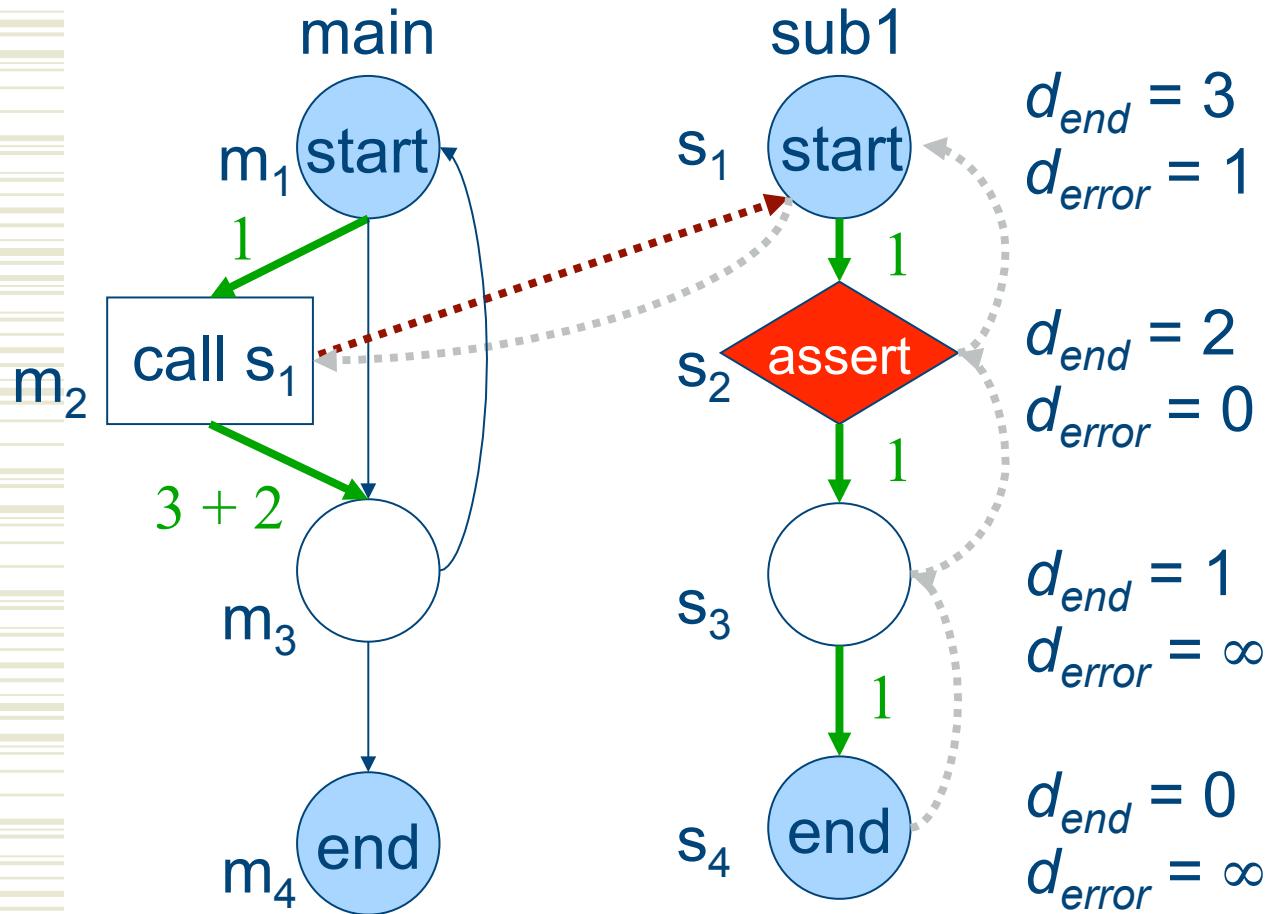
Backtrack at end nodes



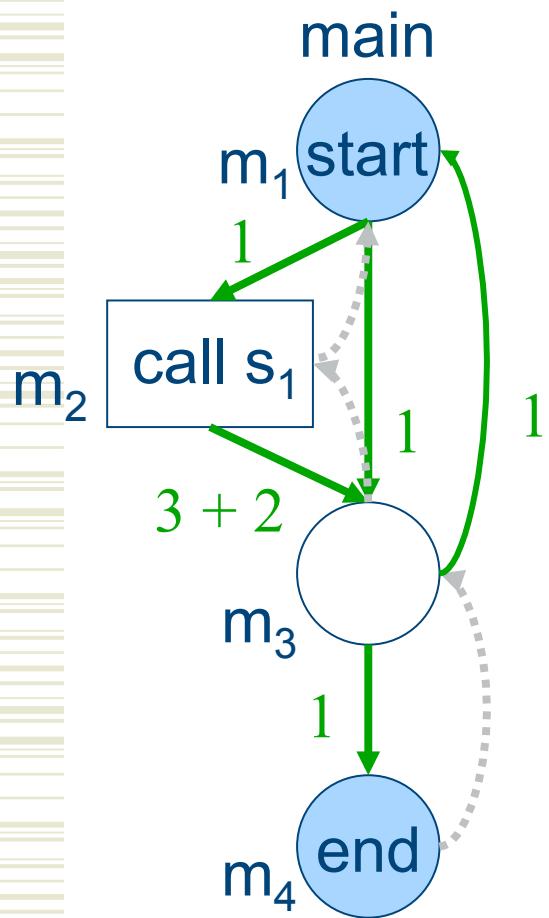
All-pairs Analysis out of Start



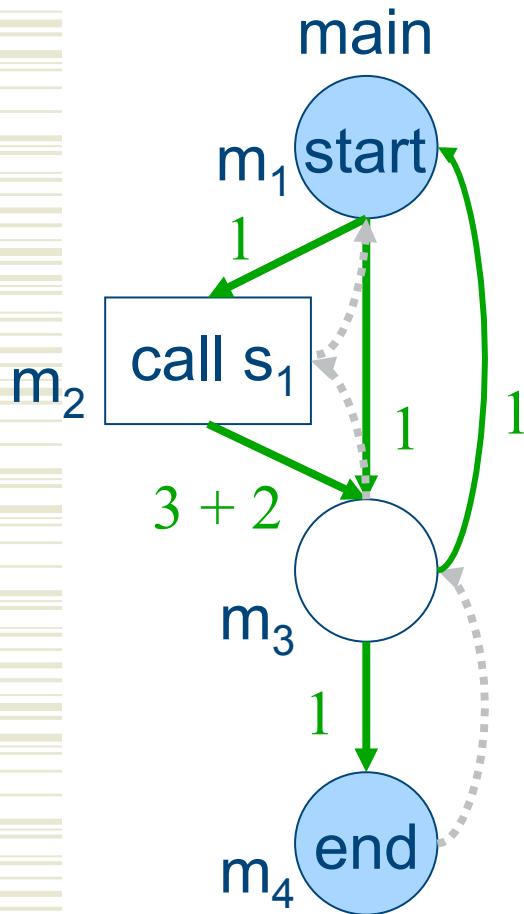
Move Cost of Call to Call-site



Continue Traversal



Trigger All-pairs on Main CFG



$$d_{\text{end}} = 2$$
$$d_{\text{error}} = 3$$

$$d_{\text{end}} = 6$$
$$d_{\text{error}} = 2$$

$$d_{\text{end}} = 1$$
$$d_{\text{error}} = 4$$

$$d_{\text{end}} = 0$$
$$d_{\text{error}} = \infty$$



$$d_{\text{end}} = 3$$
$$d_{\text{error}} = 1$$

$$d_{\text{end}} = 2$$
$$d_{\text{error}} = 0$$

$$d_{\text{end}} = 1$$
$$d_{\text{error}} = \infty$$

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Complexity

- ◆ Depth-first traversal: $O(N+E)$
- ◆ N and E for all nodes and edges
- ◆ All-pairs on local CFGs: $O(N_i^3)$
- ◆ No exponential growth like the k -bound approach
- ◆ Scales better than k -bound approach
- ◆ Not limited to k anymore



Performance Analysis

- ◆ M. Dwyer, S. Person, and S. Elbaum (FSE '06)
- ◆ Understand “hardness” of benchmark
- ◆ Measure error density with depth-bounded randomized DFS
- ◆ At each DFS level, pick random successor
- ◆ Run 1000 experiments on a cluster of machines
- ◆ Count number of experiments that find error
- ◆ Error density is ratio of error discovery runs to total experiments
- ◆ Hardness is inversely proportional to error density



Super Computer

- ◆ Marylou 4 (among the top 50 supercomputers)
- ◆ 630 nodes with 2 dual core processors at 2.6GHz
- ◆ Each node has 8 GB RAM
- ◆ One hour time bound
- ◆ We get 1024 processors at a time.
- ◆ Makes testing go quickly for random experiments



Random DFS vs. e-FCA

Depth = 2 Barbershop	e-FCA	Rand DFS Min over 1000 Runs	Rand DFS Average over 1000 Runs	Error Density over 1000 runs
T = 5	814	1,570	255,720	99.2%
T = 9	1,070	2,258	47,017	92.0%
T = 15	1,448	2,988	37,195	80.3%
T = 20	1,767	3,844	69,445	22.5%
T = 30	2,401	4,412	5,161	2.00%
T = 40	3,736	3,894	5,135	0.30%



Guided Search Results

- ◆ FCA estimates used with runtime trace is e-FCA
- ◆ Use the gnu-debugger based model checker Estes
- ◆ Benchmark set of programs with concurrency errors
- ◆ Pentium III, 1.5 GHz processor with 2 GB of RAM

- ◆ NOTE: Still depend on default search order because we do not randomize ties in priority queue



Time in seconds: Static analysis

Model	FSM	EFSM	e-FCA
Hyman (2) K=1 max=3	0	3	0
Hyman (2) K=1 max=4	1	11	0
Hyman (2) K=1 max=5	1	27	0
Dining Phil (3) K=1 max=2	1	76	0
Dining Phil (3) K=1 max=3	1	146	0
Dining Phil (3) K=0 max=4	1	4	1
Dining Phil (3) K=0 max=5	2	7	1



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States Generated before Error Discovery

Model	FSM	EFSM	e-FCA
Hyman (2) K=1 max=3	10,227	7,160	3,817
Hyman (2) K=1 max=4	41,791	21,909	13,529
Hyman (2) K=1 max=5	123,743	59,951	38,745
Dining Phil (3) K=1 max=2	53,897	4,594	1,626
Dining Phil (3) K=1 max=3	54,725	13,830	3,816
Dining Phil (3) K=0 max=4	186,419	36,467	13,696
Dining Phil (3) K=0 max=5	334,198	400,474	55,876



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Model	FSM	EFSM	e-FCA
Hyman (2) K=1 max=3	10,227	7,160	3,817
Hyman (2) K=1 max=4	41,791	21,909	13,529
Hyman (2) K=1 max=5	123,743	59,951	38,745
Dining Phil (3) K=1 max=2	53,897	4,594	1,626
Dining Phil (3) K=1 max=3	54,725	13,830	3,816
Dining Phil (3) K=0 max=4	186,419	36,467	13,696
Dining Phil (3) K=0 max=5	334,198	400,474	55,876



Time taken in seconds before Error Discovery

Model	FSM	EFSM	e-FCA
Hyman (2) K=1 max=3	4	6	1
Hyman (2) K=1 max=4	17	21	5
Hyman (2) K=1 max=5	49	56	16
Dining Phil (3) K=1 max=2	31	79	1
Dining Phil (3) K=1 max=3	28	155	3
Dining Phil (3) K=0 max=4	113	27	8
Dining Phil (3) K=0 max=5	178	388	32



Time taken in seconds before Error Discovery

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Barbershop: scalability across threads

Thread No	Depth =2	Depth =5	Depth=9
5	814	7,064	92,434
15	1,448	7,698	93,608
20	1,767	8,071	93,927
25	2,086	8,336	94,246
30	2,401	8,970	94,561
40	3,040	9,603	92,500



Barbershop: scalability across threads

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5	814	7,064	92,434
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Conclusions and Future Work

- ◆ e-FCA more efficient in our benchmarks
 - ◆ Has some hope to scale to larger systems
 - ◆ Works in the presence of PO reduction
-
- ◆ What else in the concrete state of use?
 - ◆ What if we increase error locations?



Questions

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