

MDD-Based Propagation of Among Constraints

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- Motivation
 - constraint programming
 - propagation based on MDDs
- MDD-propagation of *among* constraints
 - edge filtering
 - node refinement
- Experimental results
- Conclusion

Motivation

Constraint Programming applies

- systematic search and
- inference techniques

to solve combinatorial problems

Inference mainly takes place through:

- **Filtering** provably inconsistent values from variable domains
- **Propagating** the updated domains to other constraints

$$x_1 > x_2$$

$$x_1 + x_2 = x_3$$

$$\text{alldifferent}(x_1, x_2, x_3, x_4)$$

$$x_1 \in \{2\}, x_2 \in \{1\}, x_3 \in \{3\}, x_4 \in \{0\} \quad \}$$

Drawback of domain propagation

Observations:

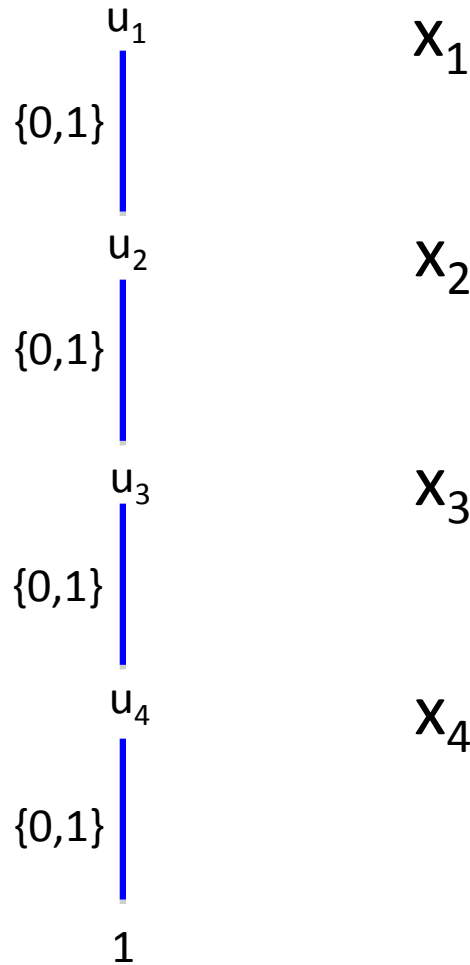
- Communication between constraints only via variable domains
- Information can only be expressed as a domain change
- Other (structural) information that may be learned by a constraint is lost: it must be projected onto variable domains
- Potential solution space implicitly defined by Cartesian product of variable domains (very **coarse relaxation**)

This drawback can be addressed by communicating more expressive information

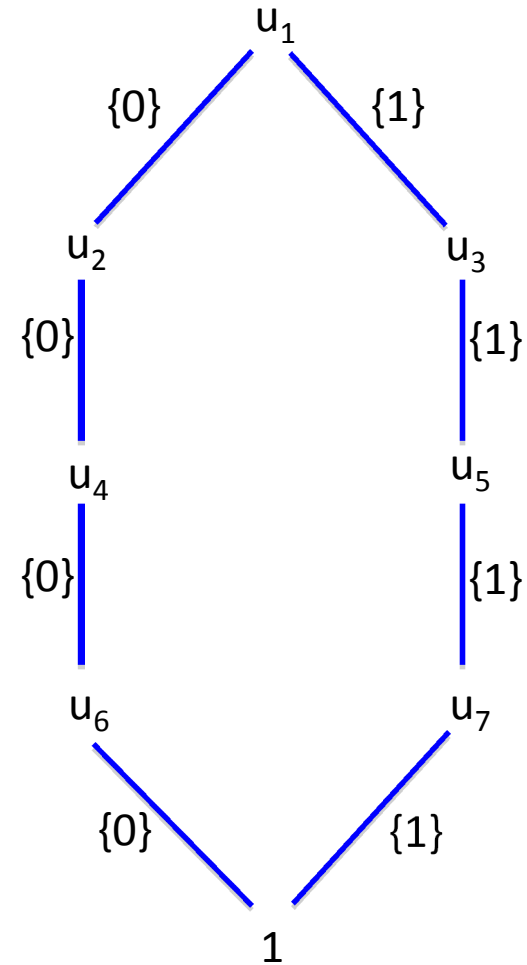
- Using *multi-valued decision diagrams* (MDDs) [Andersen et al. 2007]
- Explicit representation of **more refined** potential solution space

Illustrative Example

AllEqual(x_1, x_2, x_3, x_4), all x_i binary



domain store, size 2^4



MDD store, size 2

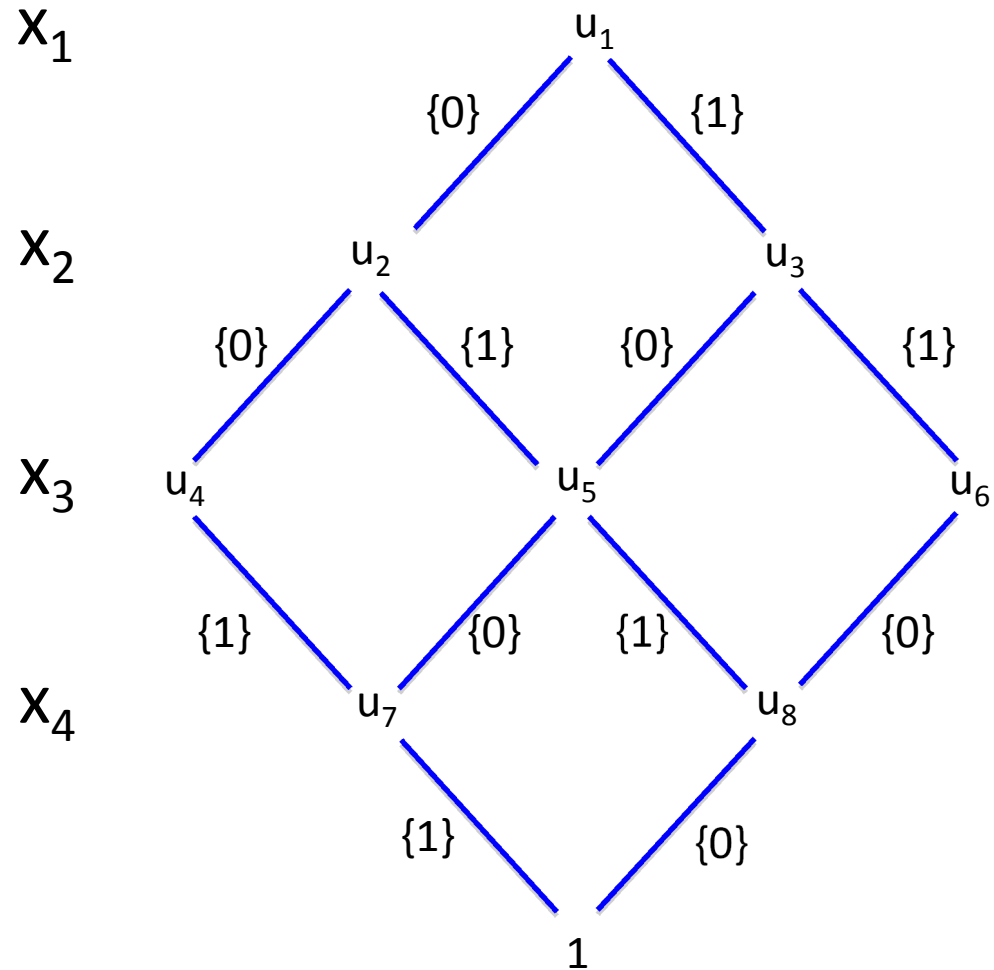
- Given a set of variables X , and a set of values S , a lower bound L and upper bound U ,

$$\text{among}(X, S, L, U) := L \leq \sum_{x \in X} (x \in S) \leq U$$

“among the variables in X , at least L and at most U take a value from the set S ”

- Applications in, e.g., sequencing and scheduling
- WLOG assume that X are binary and $S = \{1\}$

Example: MDD for Among



Exact MDD for $\text{among}(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

- Maintain limited-width MDD
 - Serves as relaxation
 - Typically start with width 1 (domain store)
 - Dynamically adjust MDD based on constraints
- Constraint Propagation
 - Edge filtering: Remove provably inconsistent edges
 - Node refinement: Split nodes to separate edge information
- Search
 - As in classical CP, but may now be guided by MDD

MDD Filtering for Among

Goal: Given an MDD and an `among` constraint, remove *all* inconsistent edges from the MDD
(establish MDD-consistency)

Approach:

- Compute path lengths from the top node and from the bottom node
- Remove edges that are not on a path with lengths between lower and upper bound
- Complete (MDD-consistent) version
 - Maintain all path lengths; quadratic time
- Partial version (does not remove all inconsistent edges)
 - Maintain and check bounds (longest and shortest paths); linear time

Node refinement for Among

For each layer in MDD, we first apply edge filter,
and then try to **refine**

- consider incoming edges for each node
- split the node if there exist incoming edges that are not equivalent (w.r.t. path length)

Example:

- We will propagate $\text{among}(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$ through a BDD of maximum width 3

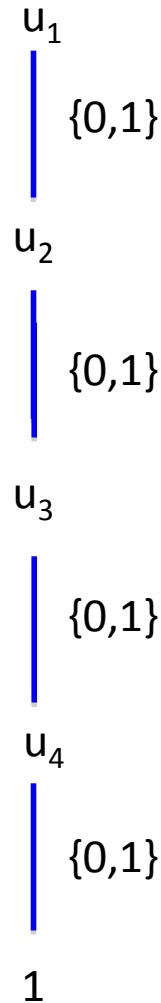
Example

Try to filter edge domain (u_1, u_2)

SP using $(u_1, u_2, \{0,1\})$ has length $< U$

LP using $(u_1, u_2, \{0,1\})$ has length $> L$

Can't filter



among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

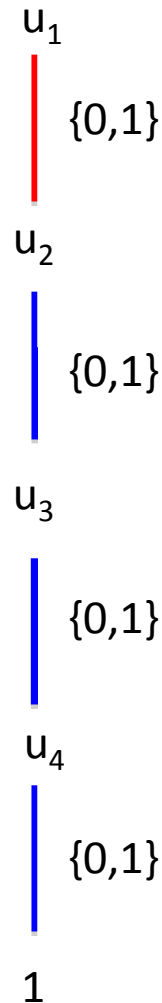
Example

Split u_2 ?

SP using $(u_1, 0) = 0$

SP using $(u_1, 1) = 1$

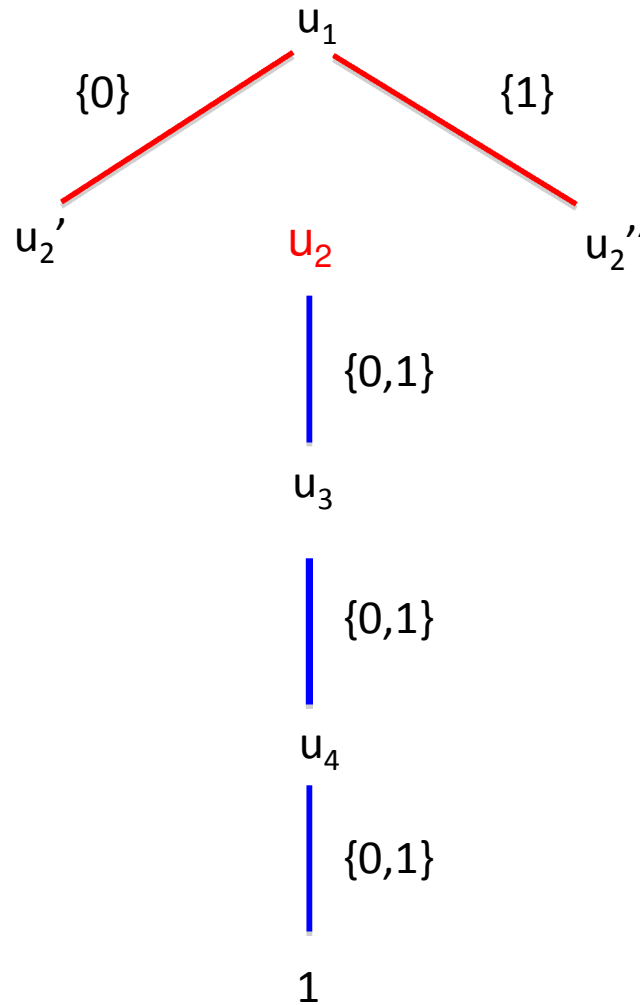
**Incoming edge-value pairs
are not equivalent: so split u_2**



among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

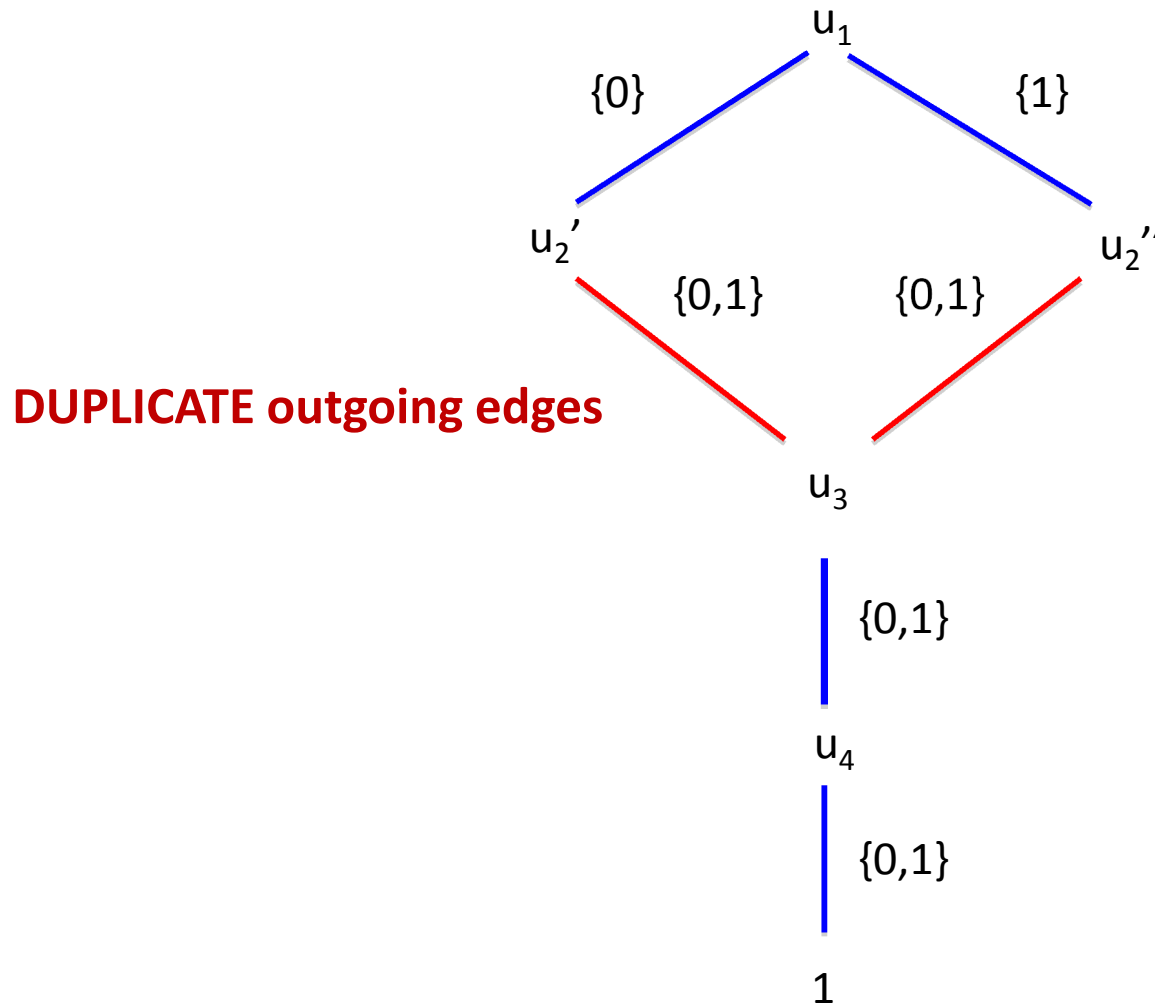
Example

**SPLIT u_2 into two classes
 (less than maximum width)**



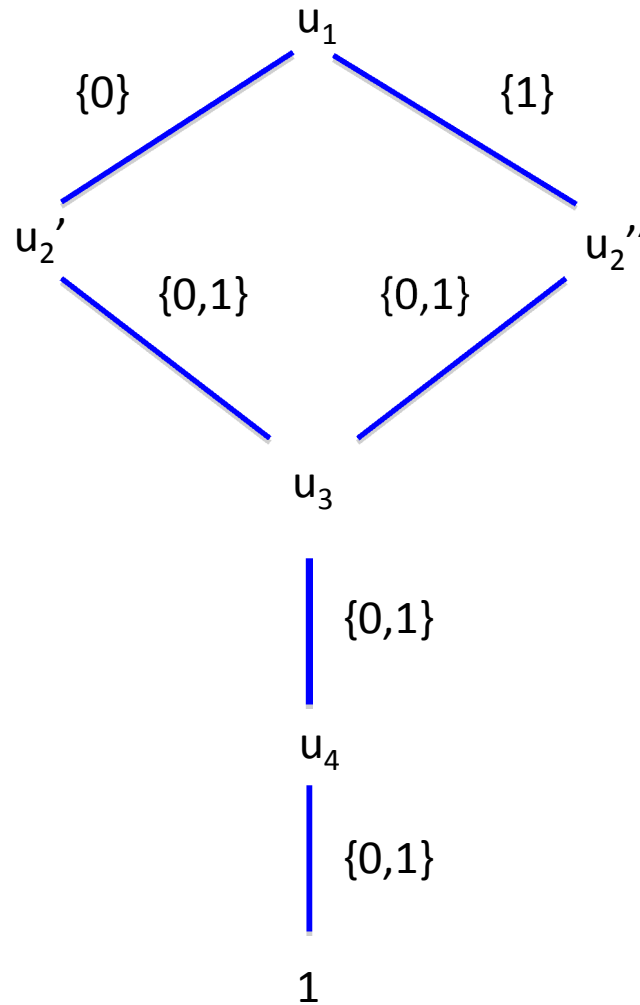
among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

Example



among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

Example

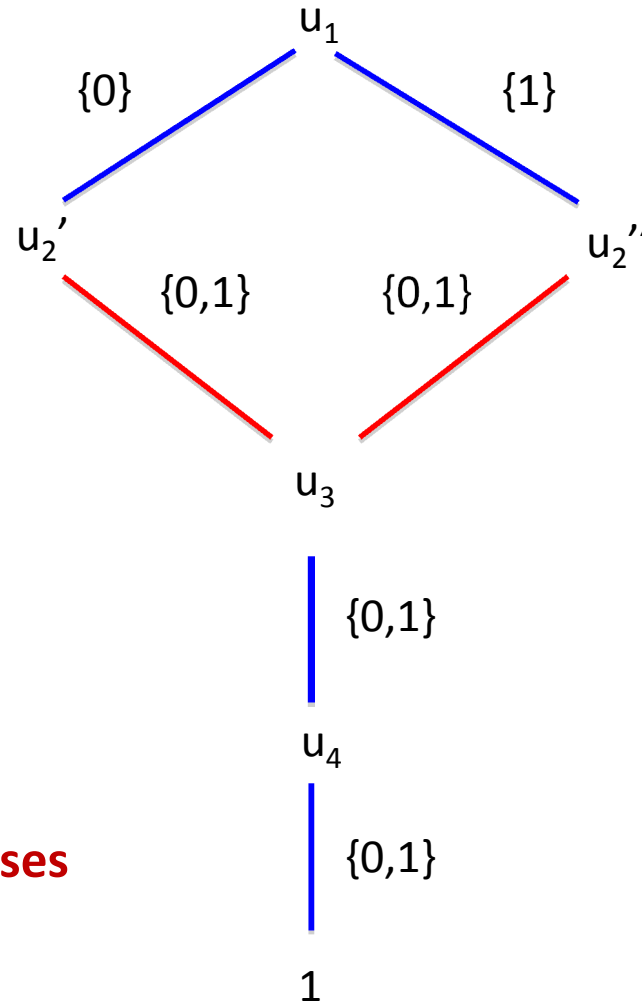


Filter edge domains
 (u_2', u_3) and (u_2'', u_3)

(No filtering possible)

among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

Example



Split u_3 ?

$$SP(u_2', u_3, 0) = 0$$

$$SP(u_2', u_3, 1) = 1$$

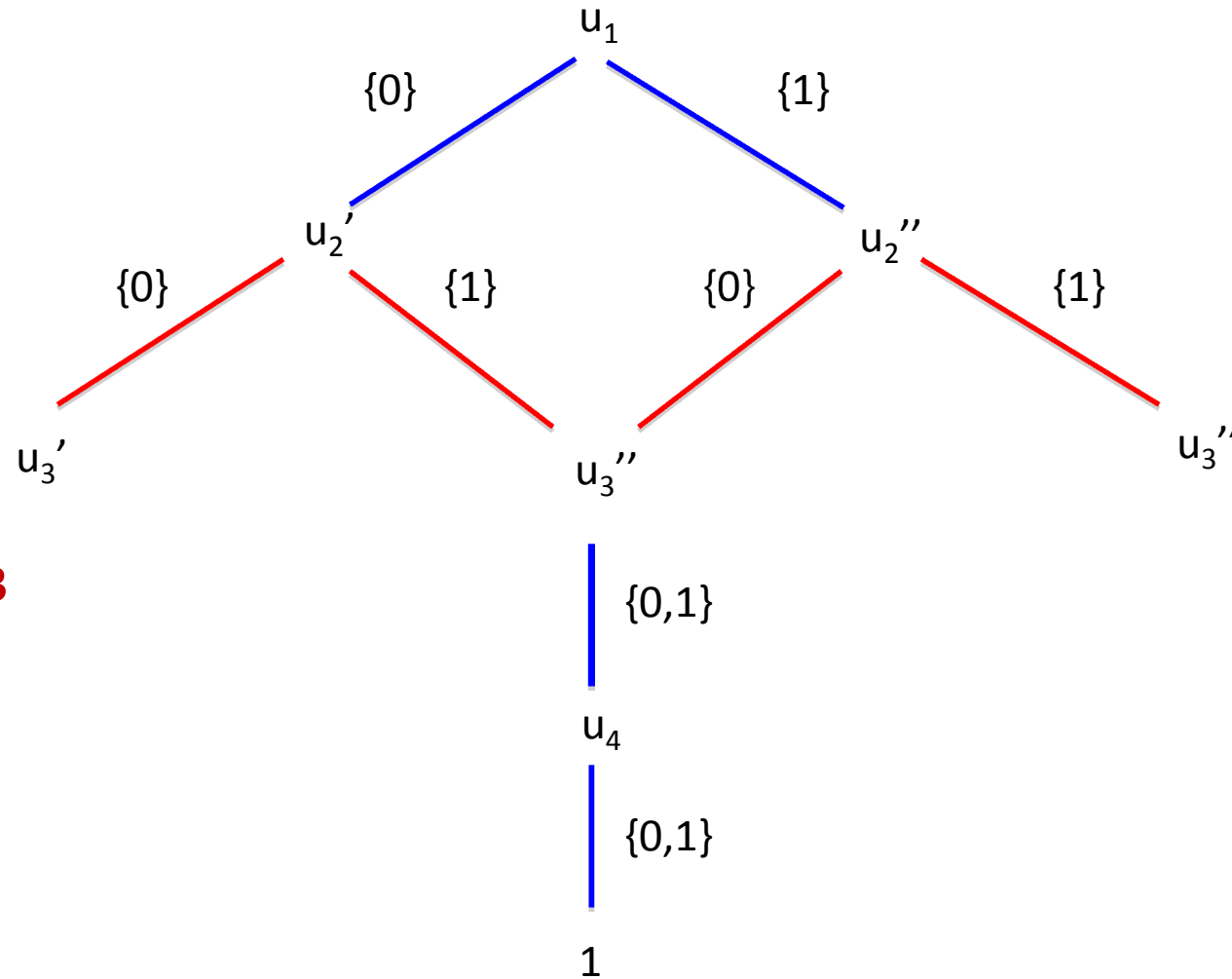
$$SP(u_2'', u_3, 0) = 1$$

$$SP(u_2'', u_3, 1) = 2$$

**Split u_3 into 3
equivalence classes**

among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

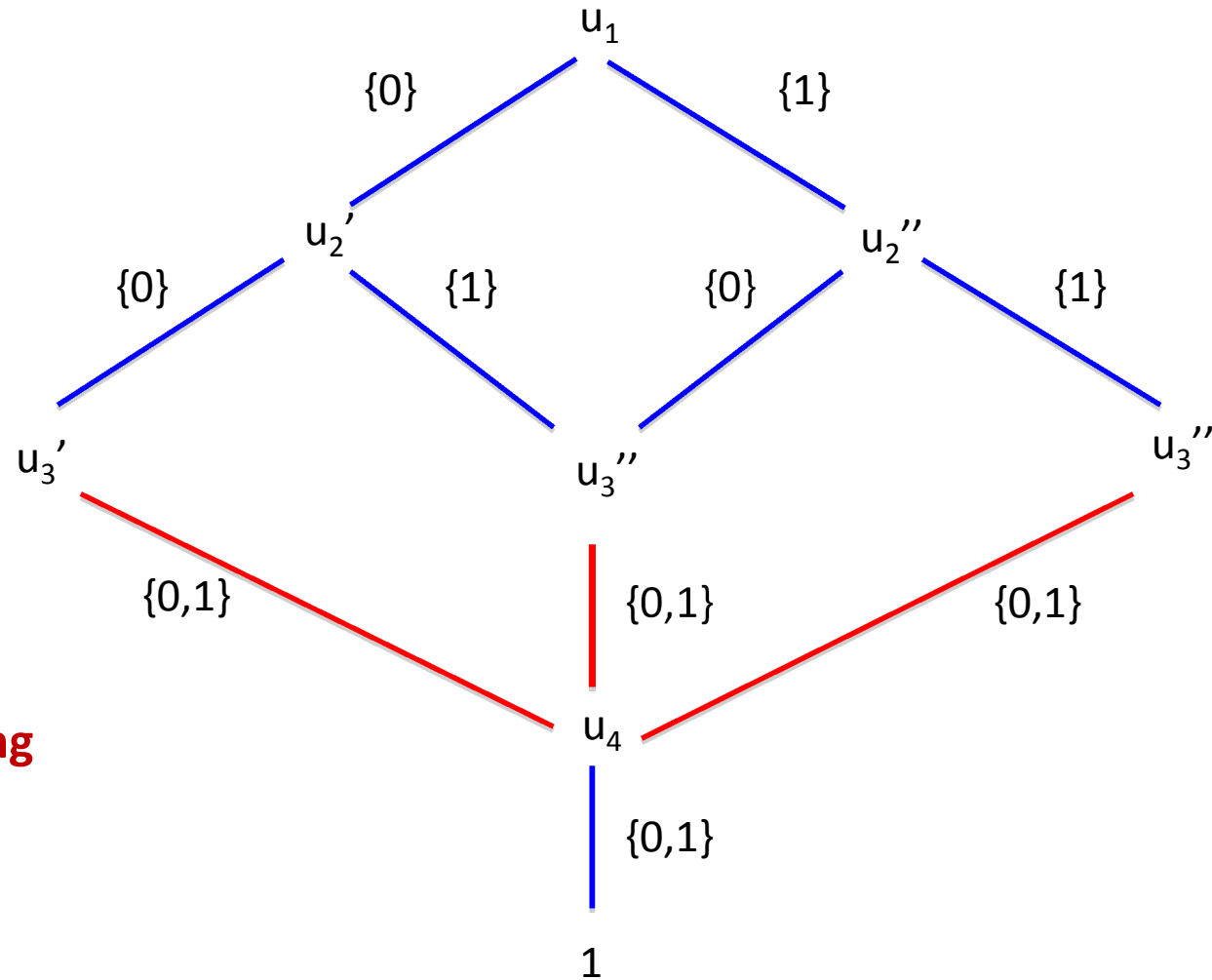
Example



**Split u_3 into 3
equivalence
classes**

among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

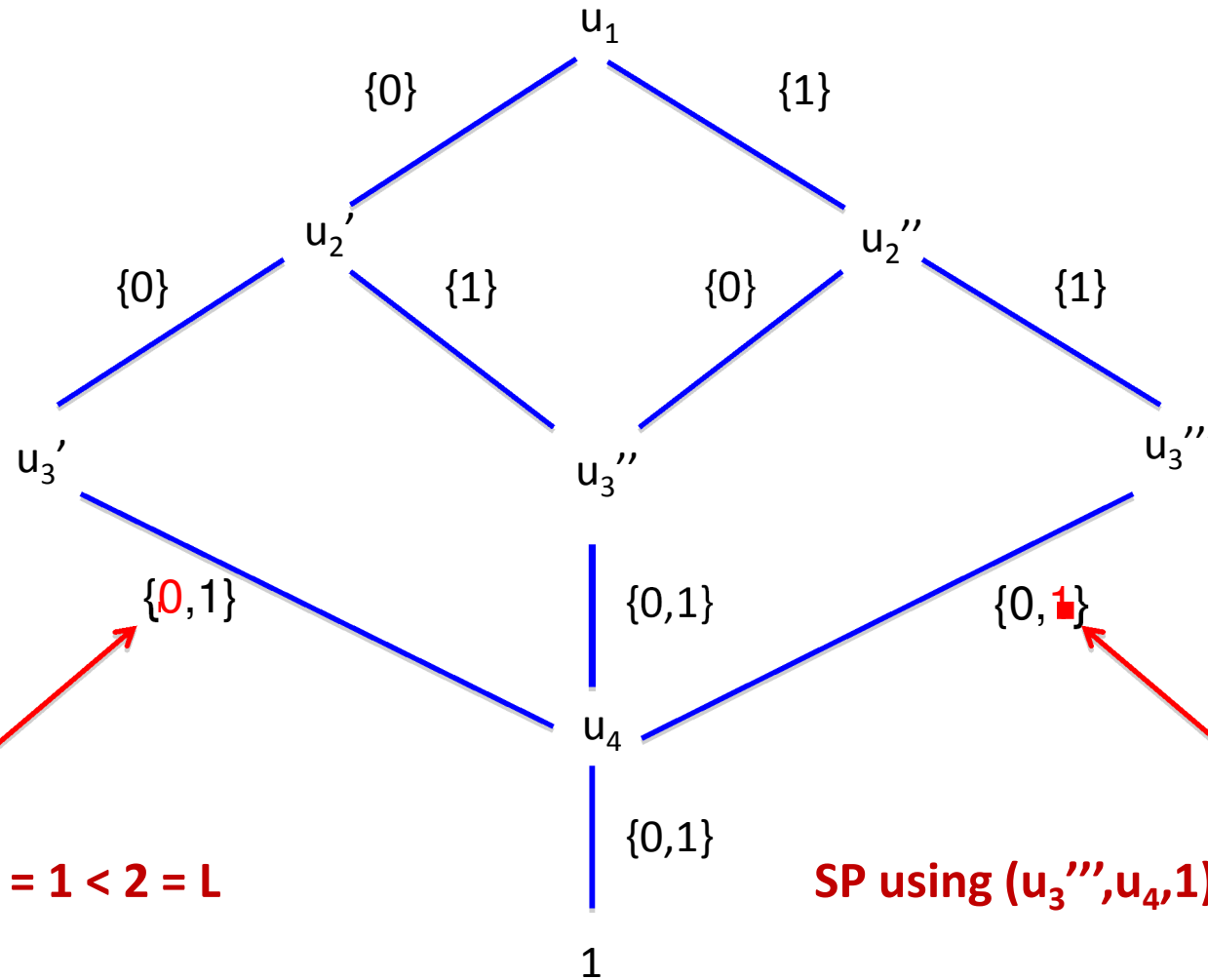
Example



Duplicate outgoing
edges

among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

Example



Filter edge domains

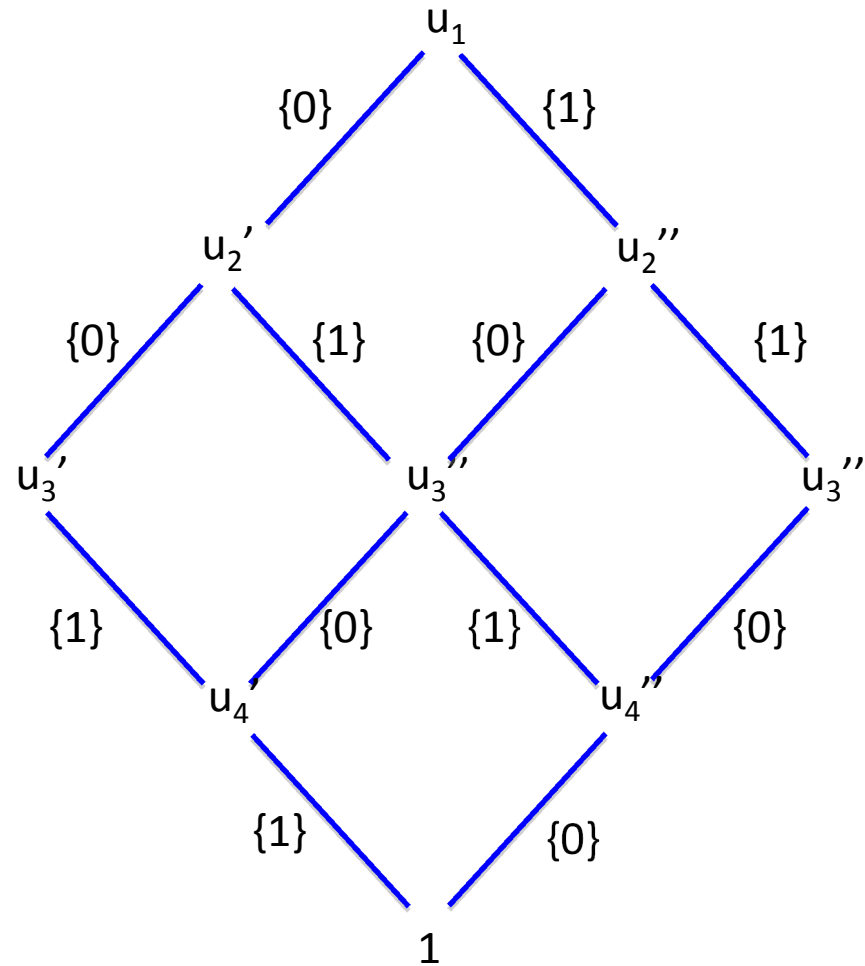
LP using $(u_3', u_4, 0) = 1 < 2 = L$

SP using $(u_3''', u_4, 1) = 3 > 2 = U$

among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

Example

Continuing...



among $(\{x_1, x_2, x_3, x_4\}, \{1\}, 2, 2)$

Example: edge-value equivalence was exact

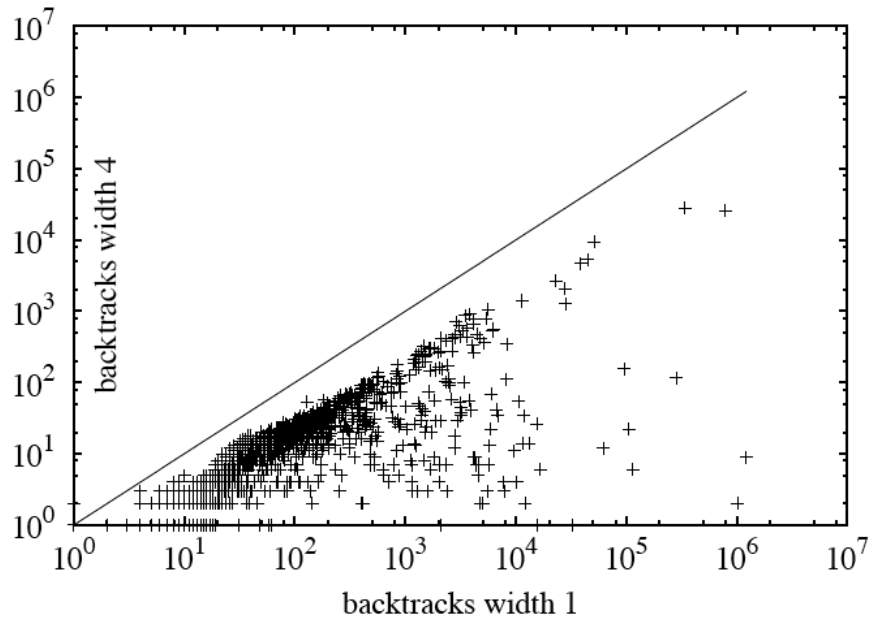
- Problem: a few nodes “consume” BDD when processing a constraint

Remedy: **approximate equivalence**

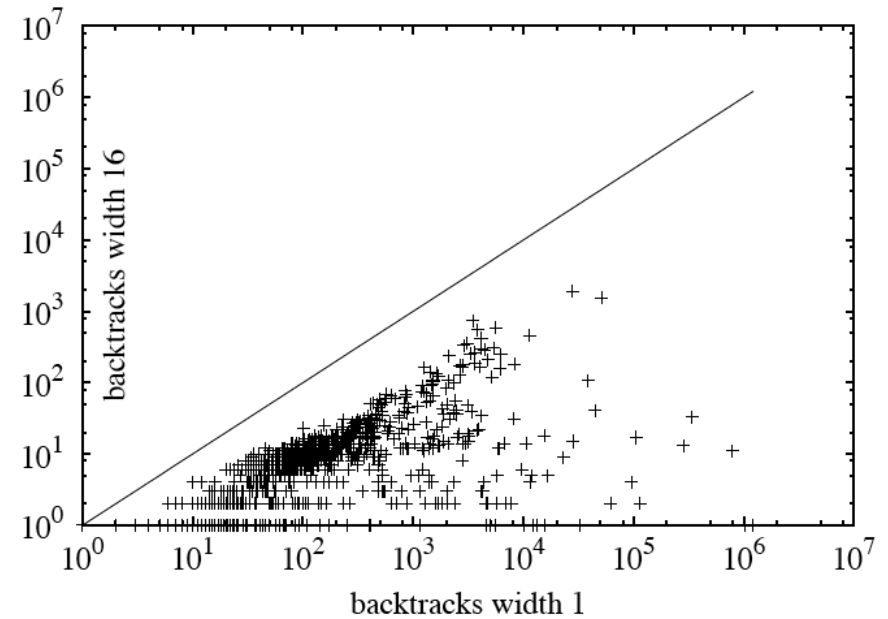
- Edge-value pairs are equivalent if SPs/LPs differ by at most some threshold value

- **Multiple among constraints**
 - 50 binary variables total
 - 5 variables per among constraint, indices chosen from normal distribution with uniform-random mean in [1..50] and stdev 2.5, modulo 50
 - Classes: 5 to 200 among constraints (step 5), 100 instances per class
- **Nurse rostering instances** (horizon n days)
 - Work 4-5 days per week
 - Max A days every B days (Max A/B)
 - Min C days every D days (Min A/B)
 - Three problem classes
- Compare width 1 (domain store) with increasing widths

Multiple Amongs: Backtracks

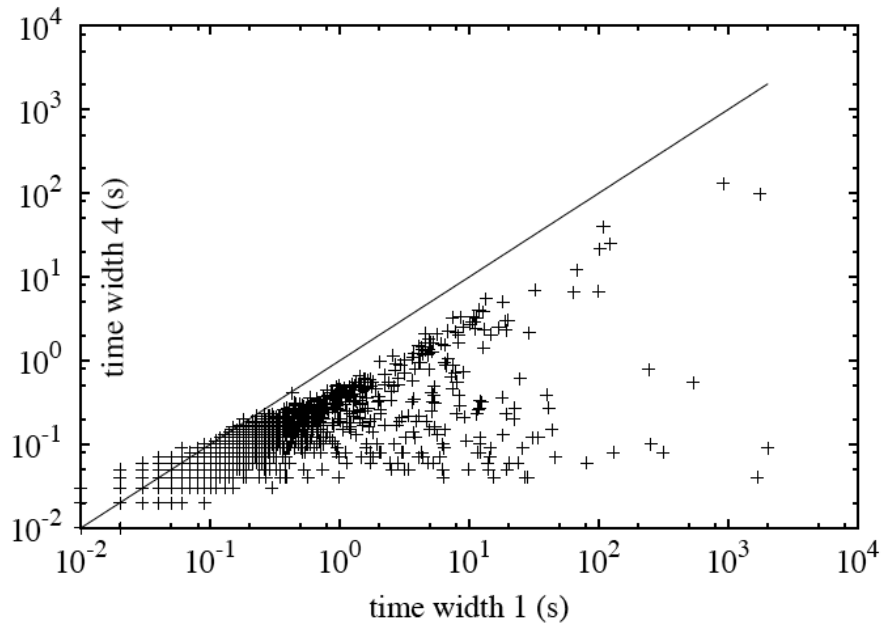


width 1 vs 4

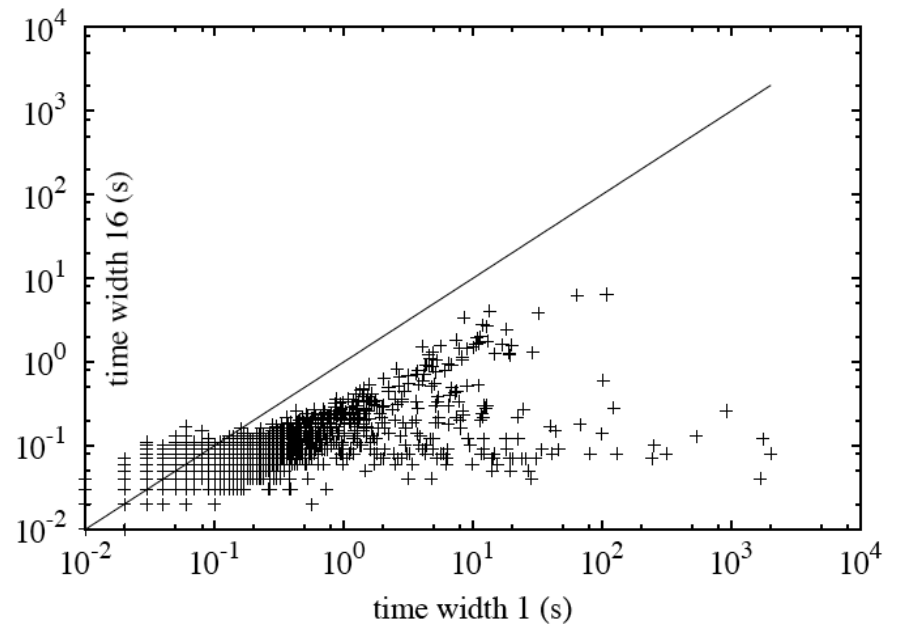


width 1 vs 16

Multiple Amongs: Running Time



width 1 vs 4



width 1 vs 16

Nurse rostering problems

	Size	Width 1		Width 4		Width 32	
		BT	CPU	BT	CPU	BT	CPU
Class 1	40	61,225	55.63	8,138	12.64	3	0.09
	80	175,175	442.29	5,025	44.63	11	0.72
Class 2	40	179,743	173.45	17,923	32.59	4	0.07
	80	179,743	459.01	8,747	80.62	2	0.32
Class 3	40	91,141	84.43	5,148	9.11	7	0.18
	80	882,640	2,391.01	33,379	235.17	55	3.27

Conclusion

- MDD store provides substantial advantage over domain store for filtering multiple among constraints
 - Wider MDDs yield greater speedups
 - Huge reduction in the amount of backtracking and solution time
- Intensive processing at search nodes can pay off when more structural information is communicated between constraints