

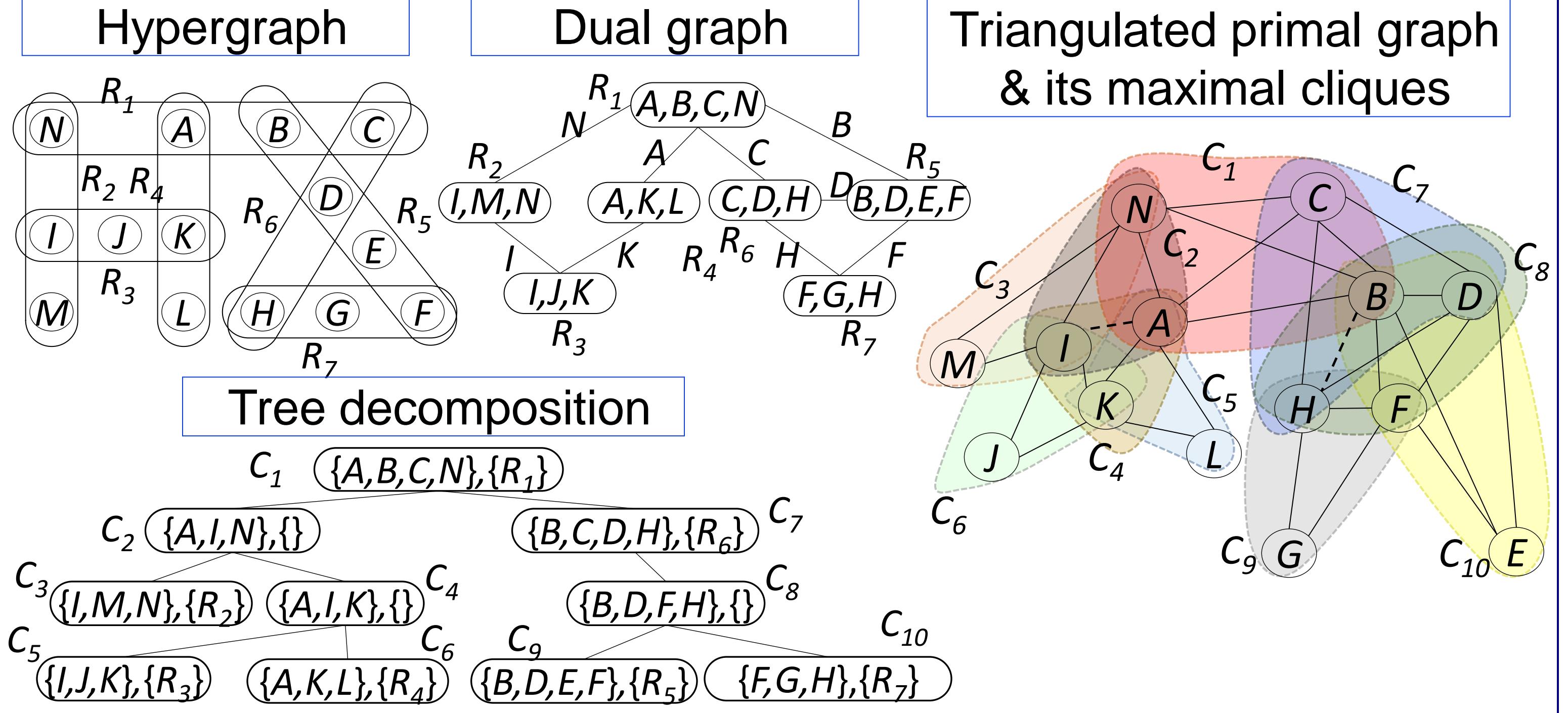
Improving the Performance of Consistency Algorithms by Localizing and Bolstering Propagation in a Tree Decomposition

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Contributions

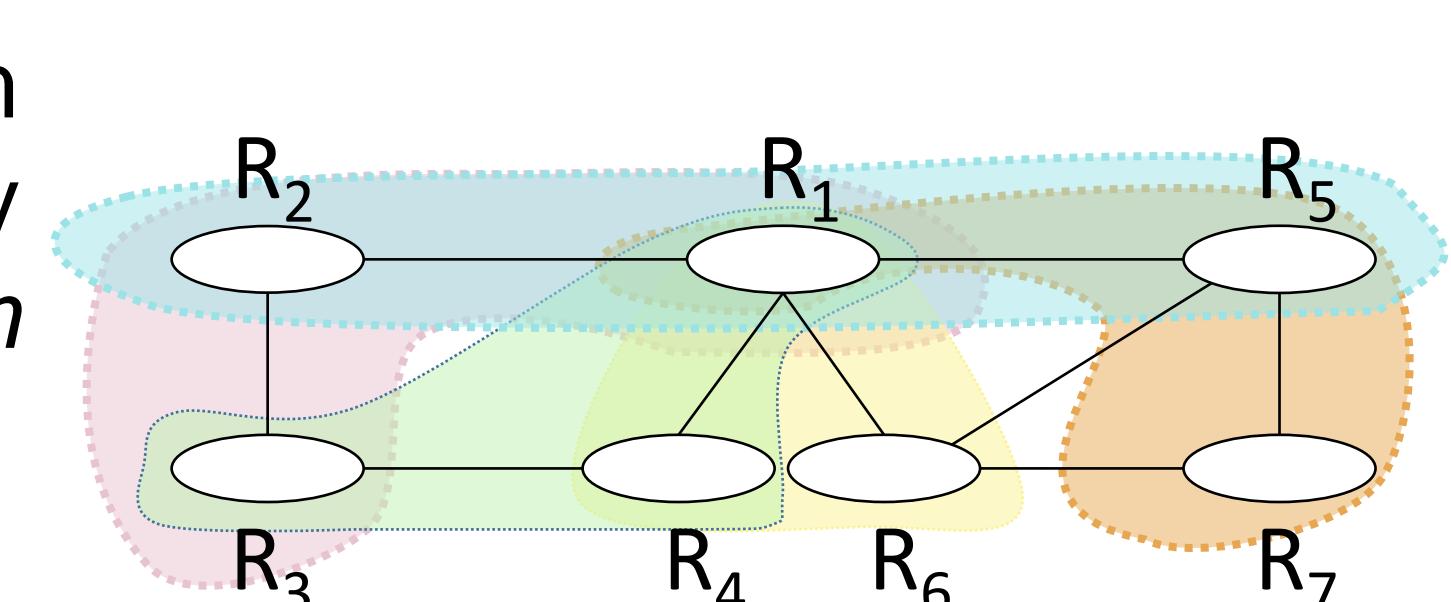
1. Localizing consistency to the clusters of a tree decomposition of a CSP & bolstering propagation at the separators between clusters
2. Theoretical characterization of resulting new consistency properties
3. Empirical evaluation of our approach establishing its benefits on difficult benchmarks, solving many problems in a backtrack-free manner and, thus, approaching ‘practical tractability’

Graphical Representation

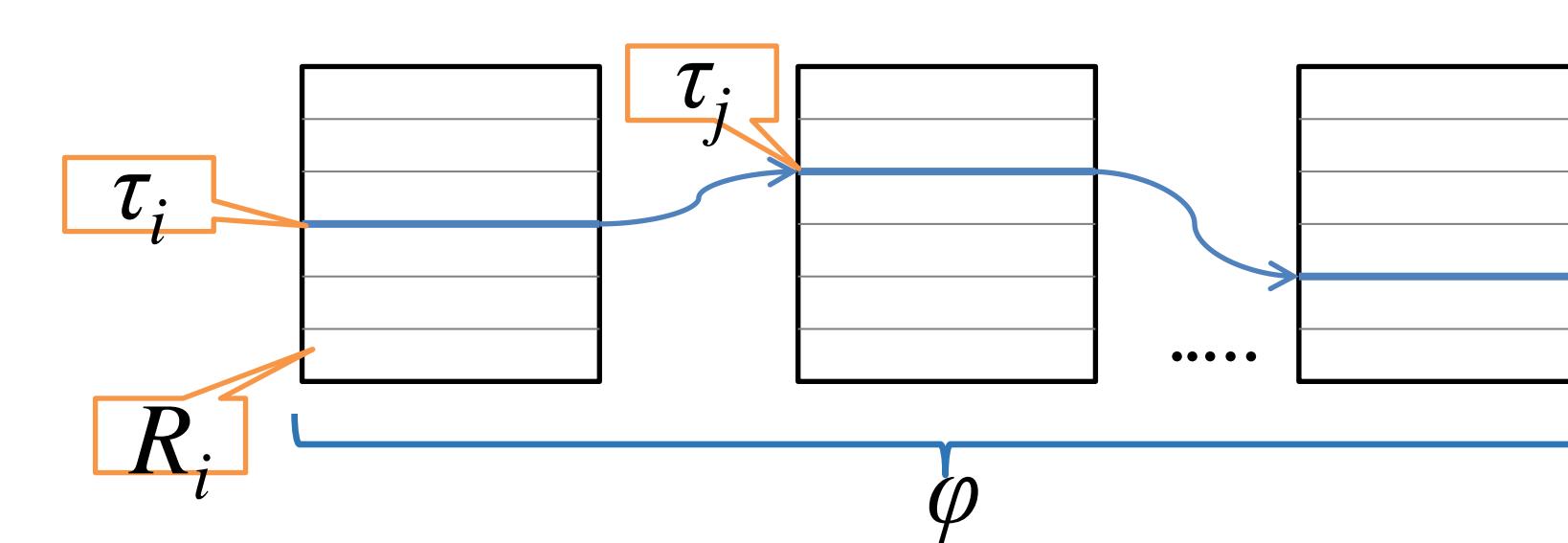


Relational Consistency

$R^{(*,m)}$ ensures that subproblem induced in the dual CSP by every connected combination of m relations is minimal [Karakashian+ 2010]

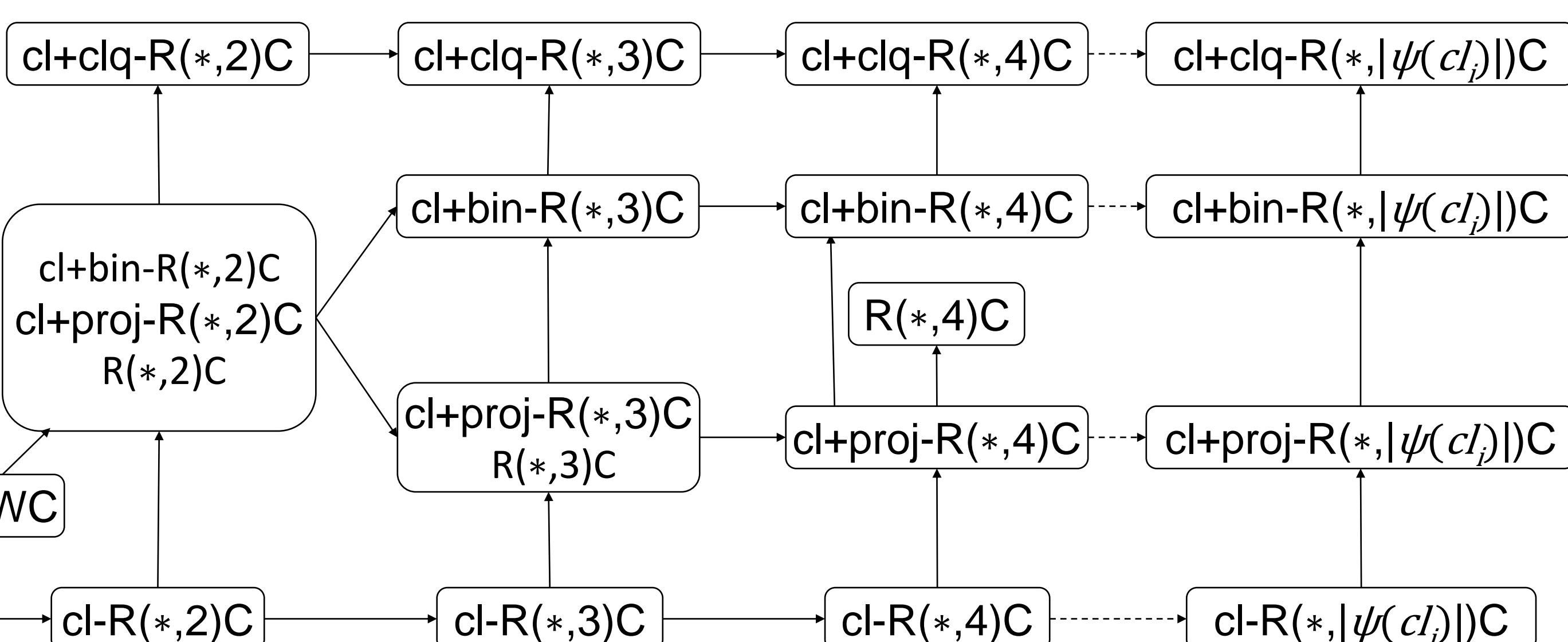


- Number of combinations = $O(e^m)$
- Size of each combination = m
- Twelve combinations for $R^{(*,3)}C$



1. {R ₁ , R ₂ , R ₃ }	7. {R ₁ , R ₄ , R ₆ }
2. {R ₁ , R ₂ , R ₄ }	8. {R ₁ , R ₅ , R ₆ }
3. {R ₁ , R ₂ , R ₅ }	9. {R ₁ , R ₅ , R ₇ }
4. {R ₁ , R ₂ , R ₆ }	10. {R ₁ , R ₆ , R ₇ }
5. {R ₁ , R ₃ , R ₄ }	11. {R ₂ , R ₃ , R ₄ }
6. {R ₁ , R ₄ , R ₅ }	12. {R ₅ , R ₆ , R ₇ }

Comparing Consistency Properties



Bolstering Propagation at Separators

Localizing $R^{(*,m)}C$

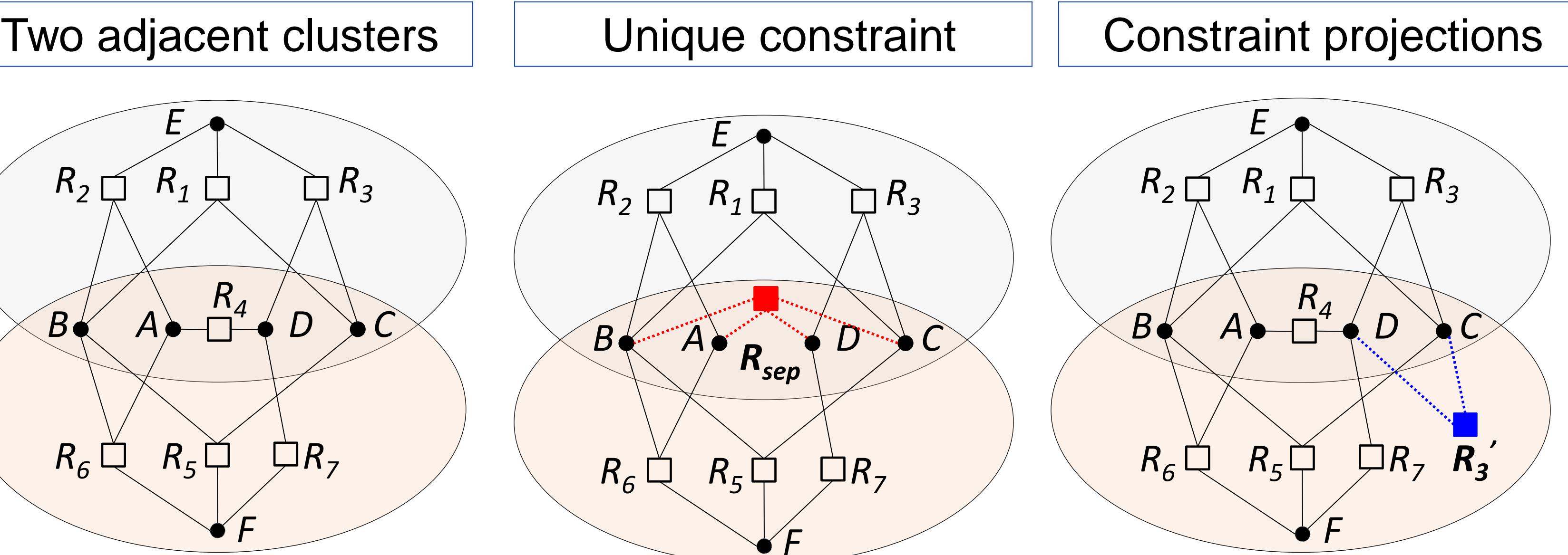
We localize the application of the consistency algorithm to each cluster of the tree decomposition, which allows us to increase the value of m to the number of relations in the cluster and, thus, the level of consistency enforced.

Bolstering Separators

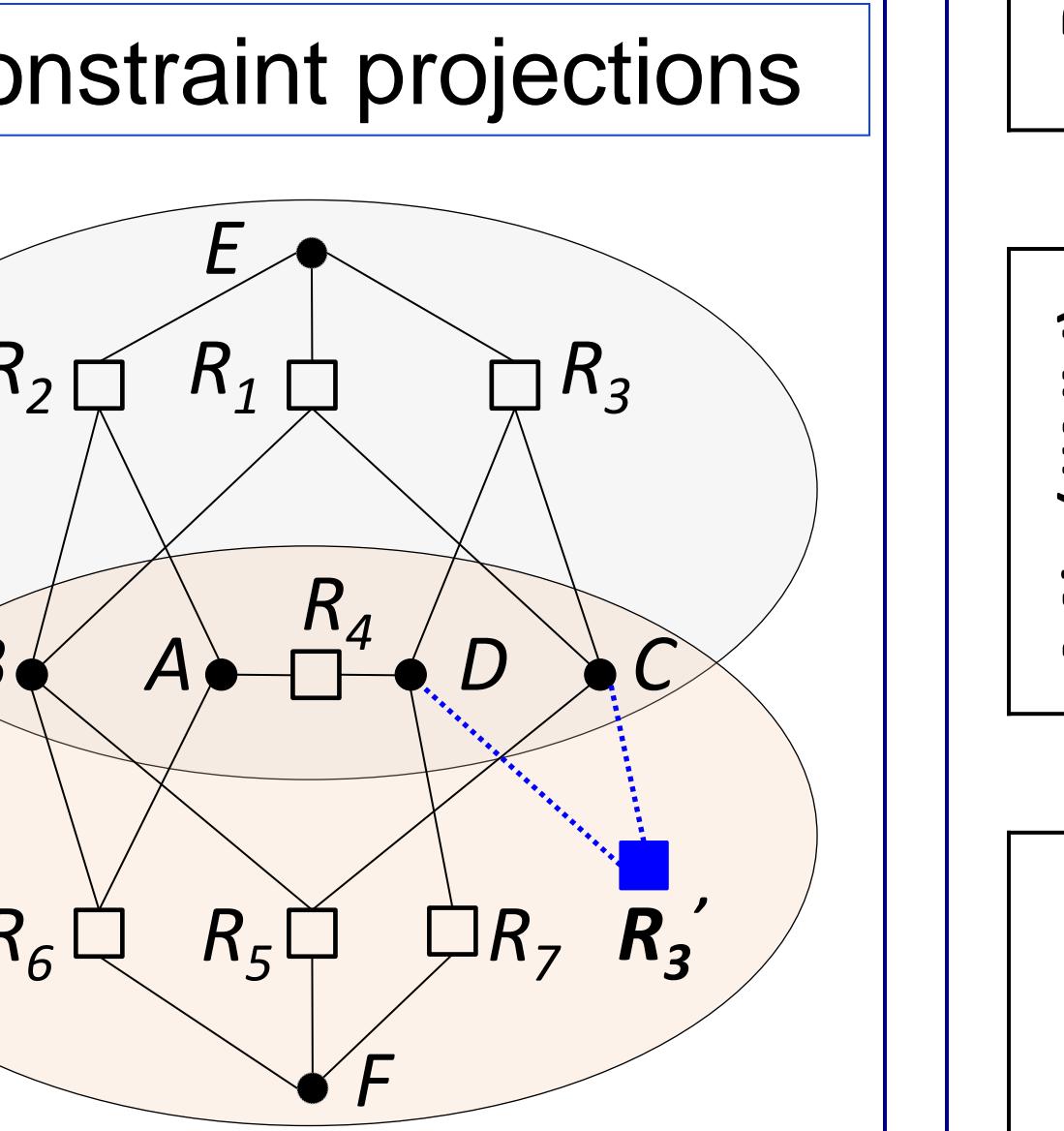
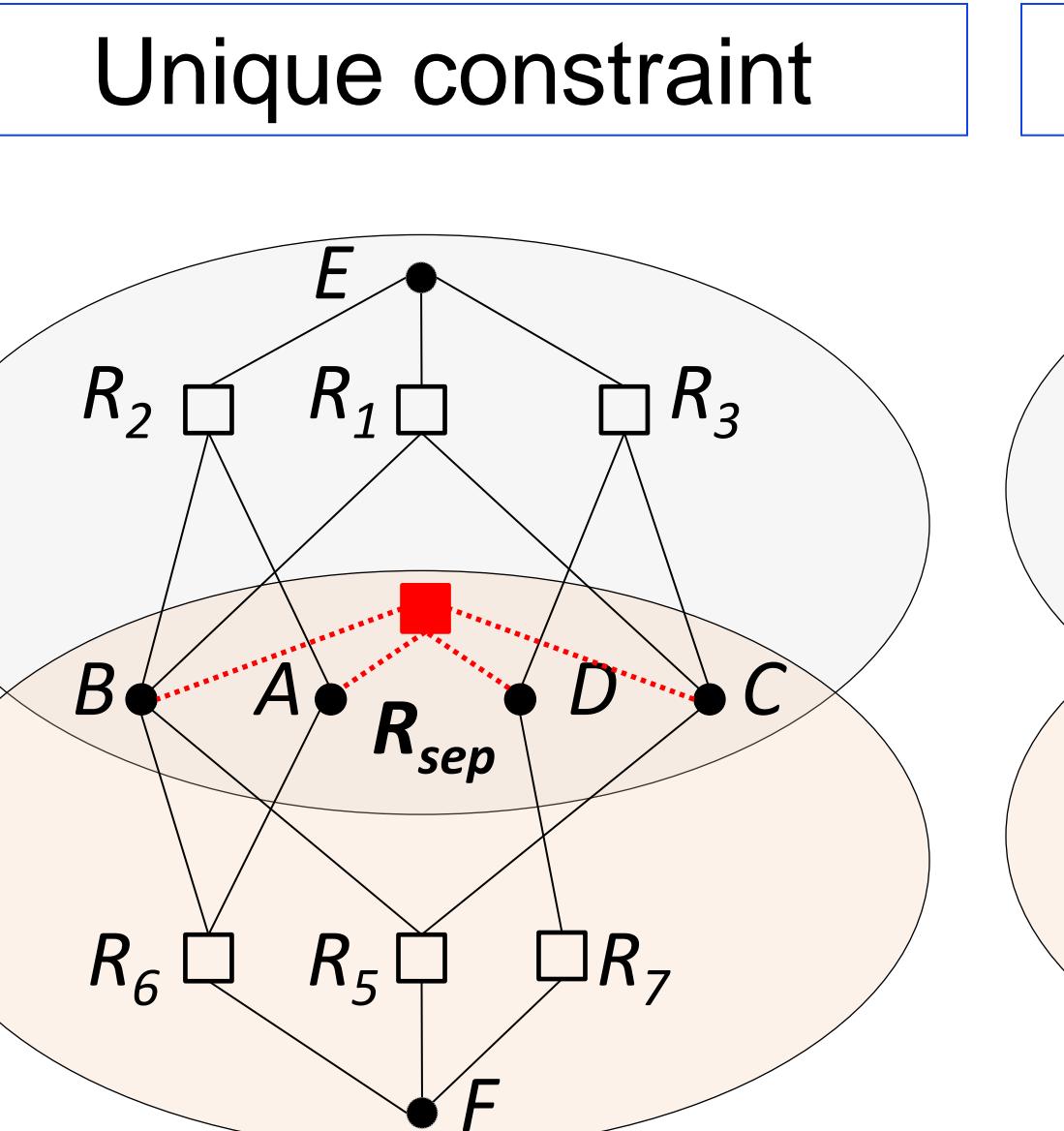
We bolster constraint propagation along the tree by adding redundant constraints to the separators.

- A perfect ‘communication’ between clusters requires a unique constraint over the separator’s variables, but materializing such a constraint is prohibitive in terms of space [Fattah and Dechter 1996; Kask+ 2005].
- We propose three approximation schemes to this end: constraint projection (proj), binary constraints (bin), clique constraints (clq).

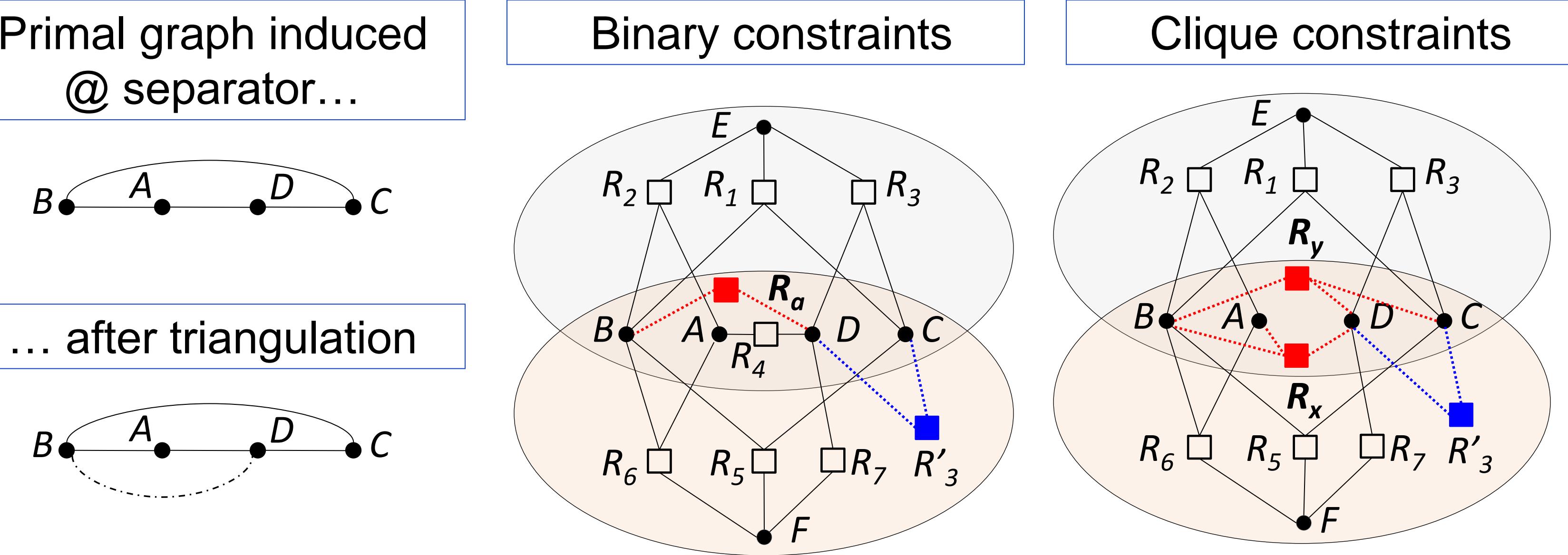
Two adjacent clusters



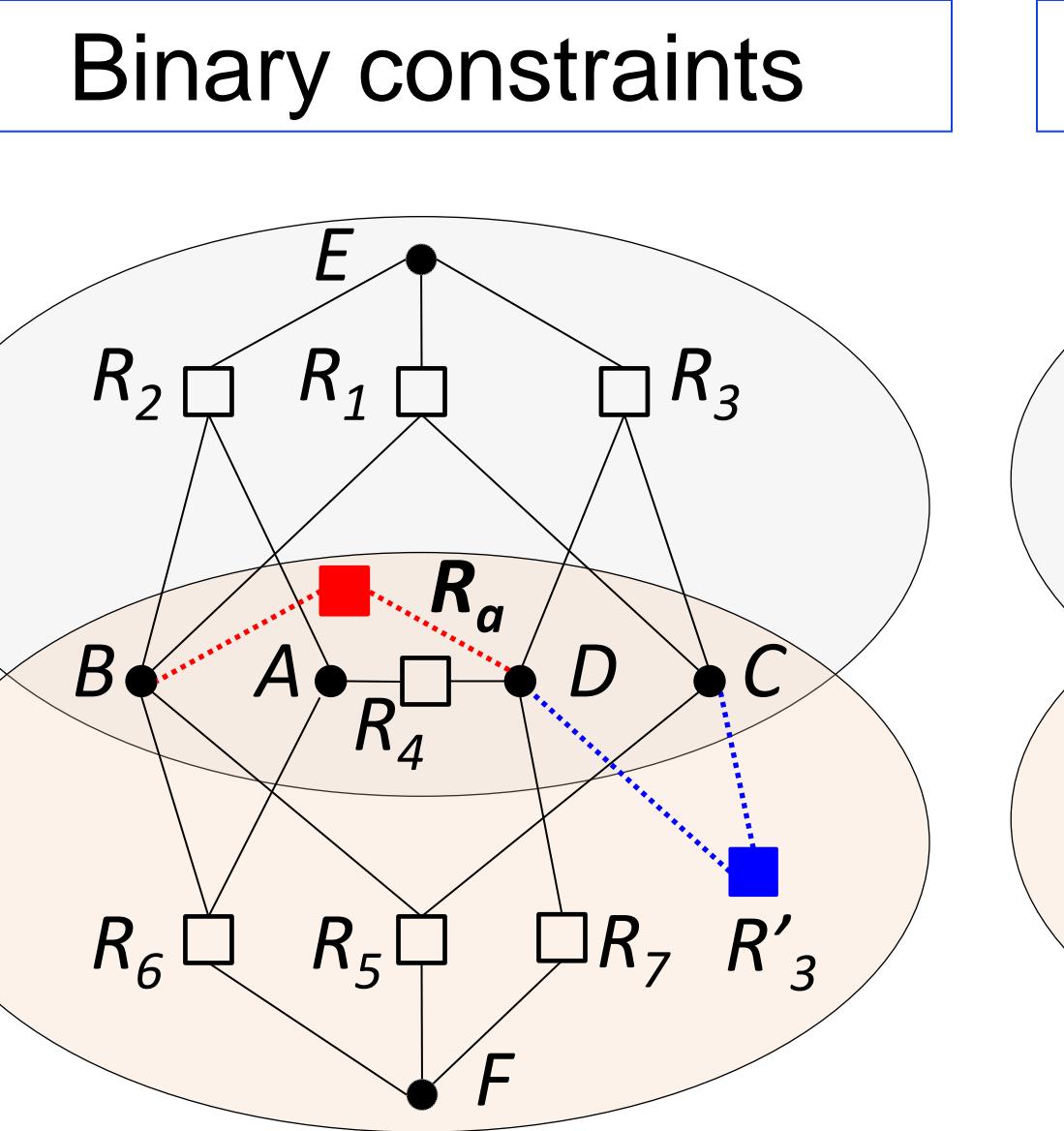
Unique constraint



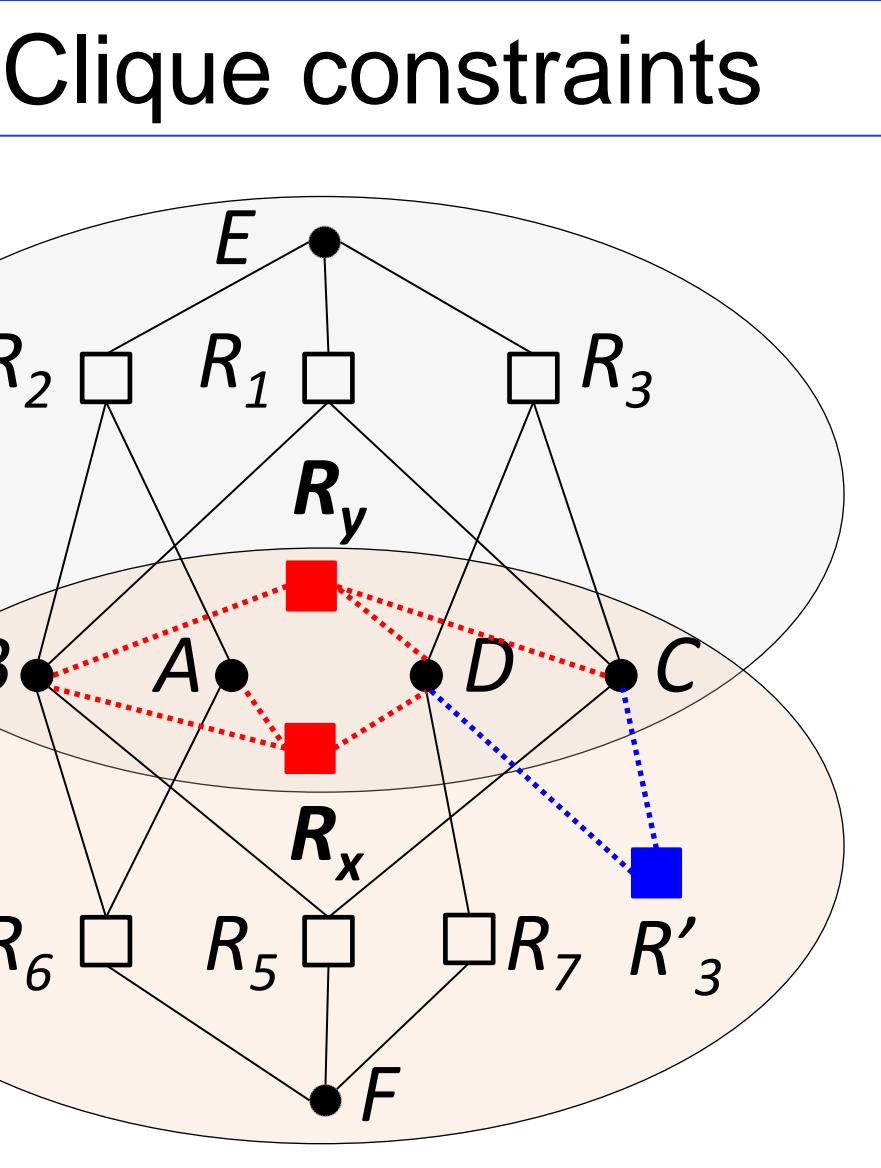
Primal graph induced @ separator...



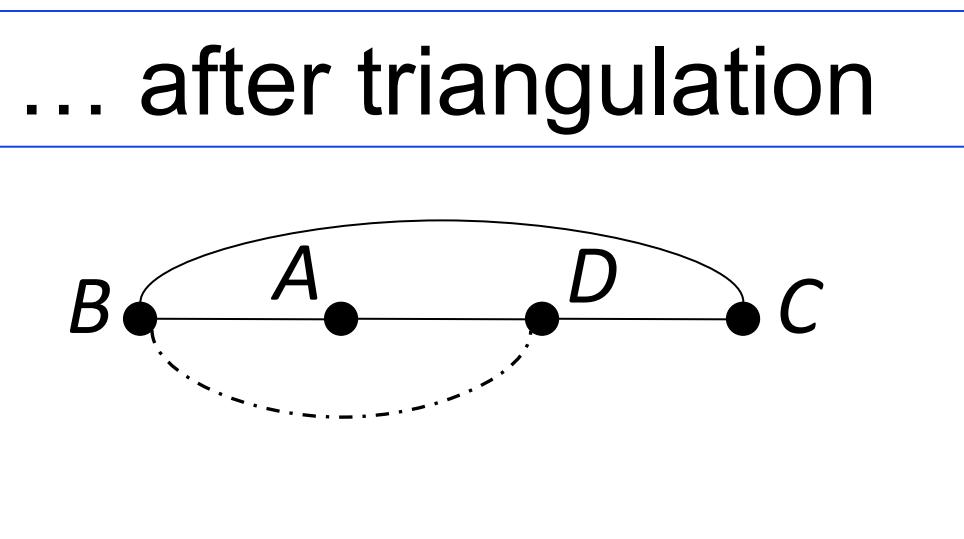
Binary constraints



Clique constraints



... after triangulation



Data Characteristics

	max		median		mean	
	UNSAT	SAT	UNSAT	SAT	UNSAT	SAT
treewidth	243	158	33	18	43.45	34.44
largest sep.	214	157	28	16.5	39.02	31.33
Max($ \psi(c_l) $)						
local	1,243	211	16	8	109.54	18.35
projection	1,243	211	18	11	114.70	37.35
binary	1,243	653	24	12	199.50	80.65
clique	1,243	148	18	10	113.35	25.87
clique arity	48	26	7	4	7.40	5.97

Empirical Evaluation

	#inst.		wR ^{(*,2)C}					R ^{(* ψ(c_l))C}			
	global	local	Proj.	binary	clique	local	Proj.	binary	clique		
Completed	UNSAT	167	170	167	172	169	162	285	286	282	
	479	34.9%	35.5%	34.9%	35.9%	35.3%	33.8%	59.5%	59.7%	56.6%	
	SAT	174	179	178	176	169	104	152	138	124	
	200	87.0%	89.5%	89.0%	88.0%	84.5%	52.0%	76.0%	69.0%	56.5%	

	#inst.		BT-Free					R ^{(* ψ(c_l))C}			
	UNSAT	SAT	0	70	39	70	70	74	187	223	213
	479	0.0%	14.6%	8.1%	14.6%	14.6%	15.4%	39.0%	46.6%	46.6%	44.5%
	SAT	44	55	37	53	52	38	39	77	71	58
	200	22.0%	27.5%	18.5%	26.5%	26.0%	19.0%	19.5%	38.5%	35.5%	29.0%

	#inst.		Min(#NV)					R ^{(* ψ(c_l))C}			
	UNSAT	SAT	17	73	43	72	72	77	220	249	239
	479	3.5%	15.2%	9.0%	15.0%	15.0%	16.1%	45.9%	52.0%	51.8%	49.9%
	SAT	47	64	37	62	61	39	41.5%	111	100	79
	200	23.5%	32.0%	18.5%	31.0%	30.5%	19.5%		55.5%	50.0%	39.5%

	#inst.		Fastest					R ^{(* ψ(c_l))C}			
	UNSAT	SAT	72	13	35	5	1	1	176	108	42
	479	15.0%	2.7%	7.3%	1.0%	0.2%	0.2%	22.5%	121	18	12
	SAT	40	45	47	23	14	12	17.0%	60.5%	9.0%	6.5%
	200	23.5%	22.5%	23.5%	11.5%	7.0%	6.0%				