

Cycle-Based Singleton Local Consistencies

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Motivation High-level consistency effectively prune search space but can be costly

Contributions

1. Exploit cycles in the constraint network of a Constraint Satisfaction Problem (CSP) to vehicle constraint propagation
2. Focus: Enforce POAC on a Minimum Cycle Basis (MCB) of the incidence graph of the CSP
3. Empirically show benefit

1. Local Consistency

Variables: $\{x_1, x_2, x_3, x_4, x_5, x_6\}$

Domains: $\{v_0, v_1, v_2, v_3\}$ for x_1, x_2, x_3 ; $\{v_1, v_2\}$ for x_4, x_5, x_6

Constraints:

R_{12}	R_{13}	R_{14}	R_{23}	R_{34}	R_{156}
x_1, x_2	x_1, x_3	x_1, x_4	x_2, x_3	x_3, x_4	x_1, x_5, x_6
v_0, v_0	v_0, v_0	v_0, v_1	v_0, v_1	v_0, v_1	v_0, v_1, v_1
v_1, v_1	v_1, v_1	v_1, v_1	v_1, v_0	v_1, v_1	v_1, v_1, v_1
v_2, v_2	v_1, v_3	v_1, v_2	v_1, v_2	v_1, v_2	v_2, v_2, v_2
v_3, v_1	v_2, v_2	v_2, v_1	v_1, v_3	v_2, v_1	v_3, v_3, v_3
v_3, v_2	v_2, v_3	v_2, v_2	v_2, v_1	v_2, v_2	
	v_3, v_1	v_3, v_2	v_2, v_3	v_3, v_2	
	v_3, v_2				
	v_3, v_3				

Generalized Arc Consistency (GAC) ensures a value in the domain of a variable in the scope of a relation can be extended to a tuple satisfying the relation.

E.g., v_3 can be removed from x_2

Singleton Arc Consistency (SAC) ensures that the CSP remains arc consistent after assigning a value to a variable.

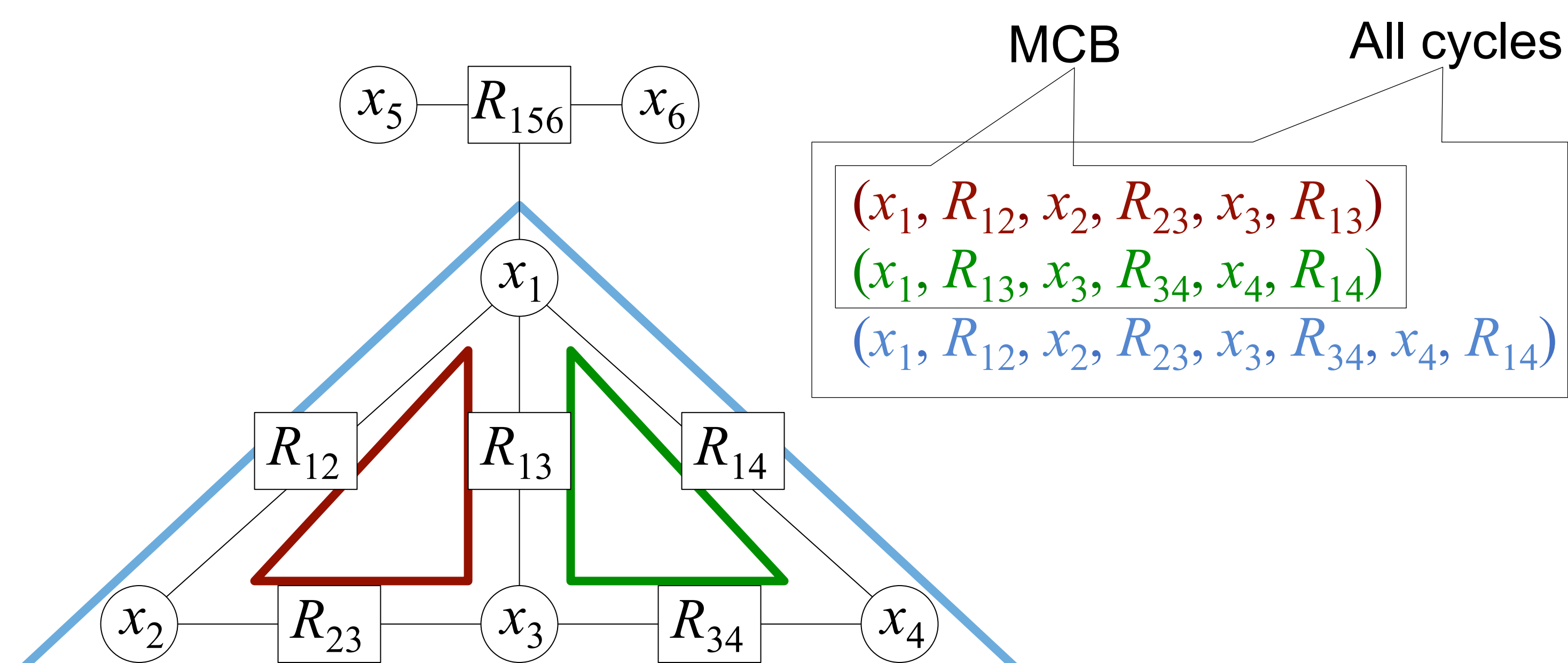
E.g., v_0 can be removed from x_1, x_2, x_3

A constraint network $\mathcal{P} = (\mathcal{X}, \mathcal{D}, \mathcal{C})$ is **Partition-One Arc-Consistent (POAC)** iff \mathcal{P} is SAC and for all $x_i \in \mathcal{X}$, for all $v_i \in \text{dom}(x_i)$, for all $x_j \in \mathcal{X}$, there exists $v_j \in \text{dom}(x_j)$ such that $(x_i, v_i) \in \text{AC}(\mathcal{P} \cup \{x_j \leftarrow v_j\})$ [Bennaceur and Affane CP 2001]

E.g., v_1 can be removed from x_4 because there is no such v_j for x_1 where $(x_4, v_1) \in \text{AC}(\mathcal{P} \cup \{x_1 \leftarrow v_j\})$.

2. Minimum Cycle Basis

Computed on incidence graph, bipartite graph $G = (\mathcal{X}, \mathcal{C}, E)$
 \mathcal{X} : variables, \mathcal{C} : constraints, E : link c_i and $x_i \in \text{scope}(c_i)$

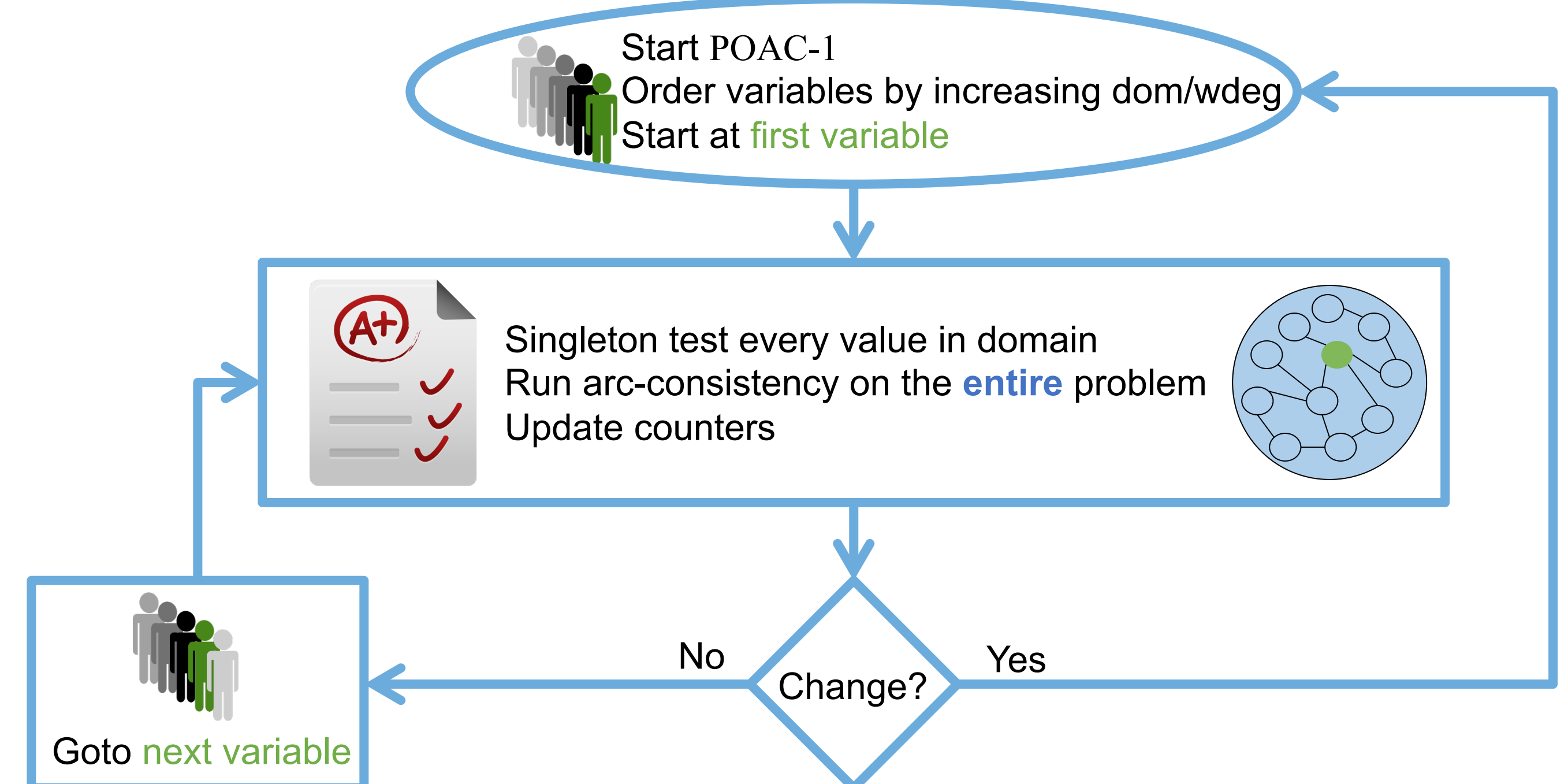


A **Minimum Cycle Basis (MCB)**: a cycle \in MCB cannot be obtained by symmetric difference from other cycles \in MCB

3. Localizing POAC

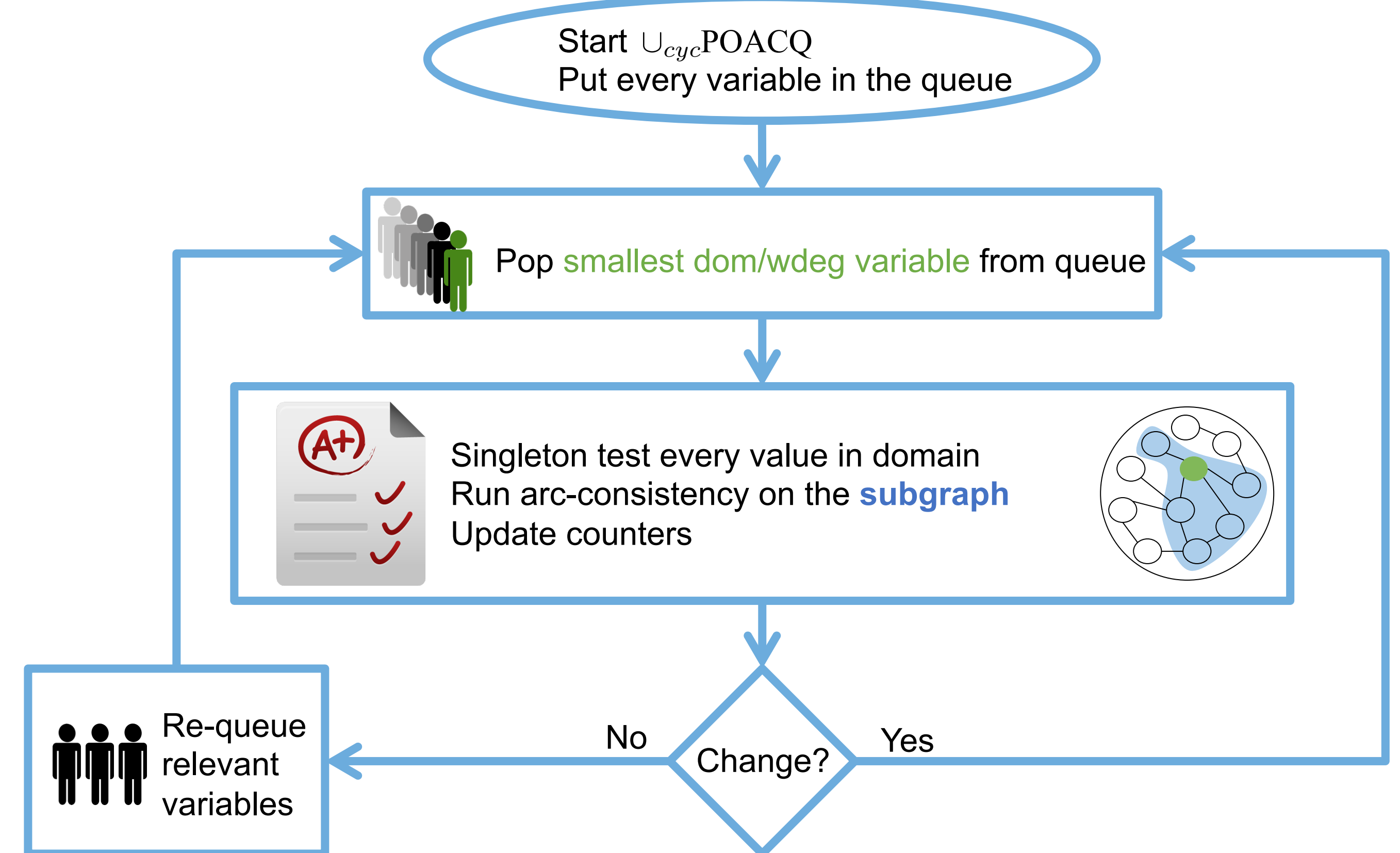
Union-Cycle POAC (\cup_{cyc} POAC): restrict the singleton test to the neighborhood of a variable and to the union of the MCB cycles in which the variable appears.

Algorithm derived from POAC-1 [Balafrej+ AAAI 2014]



We introduce \cup_{cyc} POACQ, derived from POAC-1, with two major changes:

1. Restrict the singleton test to the neighborhood union of the MCB cycles in which it appears (subgraph)
2. Use a priority queue for propagation



4. Empirical Evaluations

Benchmark		GAC	POAC	\cup_{cyc} POACQ	APOAC	$A\cup_{cyc}$ POACQ
Adaptive POAC the best						
TSP-25	# solv	15	14	15	15	15
(# inst 15)	Σ CPU (s)	4,303.12	>41,382.27	32,654.67	6,152.91	2,418.41
cril	# solv	6	7	7	8	8
(# inst 8)	Σ CPU (s)	>30,458.10	>16,282.45	>16,651.04	2,321.96	1,831.60
QWH-20	# solv	10	10	10	10	10
(# inst 10)	Σ CPU (s)	2,256.61	6,154.43	3,007.98	2,236.32	2,061.63
k-insertions	# solv	17	17	18	18	18
(#inst 32)	Σ CPU (s)	>17,034.30	>21,639.31	11,814.83	6,129.92	8,940.59
Non-adaptive POAC the best						
mug	# solv	6	6	8	6	6
(# inst 8)	Σ CPU (s)	>54,724.38	>29,385.02	13,655.87	>34,207.98	>41,583.97
GAC the best						
TSP-20	# solv	15	15	15	15	15
(# inst 15)	Σ CPU (s)	302.21	2,750.90	3,096.07	593.04	384.13
renault	# solv	50	50	50	50	50
(# inst 50)	Σ CPU (s)	55.87	277.74	176.28	196.04	155.88
myciel	# solv	13	12	12	13	13
(# inst 16)	Σ CPU (s)	1,711.93	>21,564.06	>26,196.15	3,118.86	2,555.54

5. Future Research

Extend approach to other high-level consistency algorithms