

SAT modulo Graphs: Acyclicity

Jussi Rintanen

Department of Information and Computer Science
Aalto University, Finland

(Also affiliated with Griffith University, Brisbane, Australia, and the Helsinki Institute of Information Technology, Finland.)

Joint work with *Martin Gebser and Tomi Janhunen*

September 2014

Acyclicity is required in solutions of several important problems that can be reduced to the propositional satisfiability problem SAT.

- partial-order methods in planning (Rintanen et al. 2006) and bounded LTL model-checking
- well-foundedness of inductive definitions
- rule dependencies in answer set programming
- Bayesian networks, Markov networks (the structure learning problem) (Cussens 2008; Corander et al. 2013)

More General Motivation

Many graph-related concepts difficult to encode as propositional formulas (size, efficiency).

- Which nodes **reachable** from the source node?
- Which nodes on a **simple path** between a source node and sink node?

Application in e.g. networked systems' diagnosis, control, design: telecom, electricity, water, transport

A New Class of SAT Modulo Theories Problems

SAT modulo Graphs (SMG)

standard SAT problem (a set of clauses) +

- set of **nodes**
- set of **edges/arcs**
- mapping from edges/arcs (n, n') to propositional variables $a_{n,n'}$
- **property** satisfied by **subgraph** consisting of **true** edges/arcs

In general, the property is identified with a single propositional variable that may be assigned true or false, but in this work the property is fixed to *true*.

- We will focus on **acyclicity**: how to handle SAT+acyclicity efficiently?
- space consumption **linear** in $|E| + |V|$
- strong propagations
- Outperforms other representations of acyclicity in our experiments.

- ① Run a SAT solver based on Conflict-Driven Clause Learning (CDCL).
- ② When an arc variable is assigned *true*,
 - Check whether the graph contains a cycle $n_1 \rightarrow n_2 \rightarrow \dots \rightarrow n_m \rightarrow n_1$. If it does,
 - ① generate a clause $\neg a_{n_1, n_2} \vee \neg a_{n_2, n_3} \vee \dots \vee \neg a_{n_m, n_1}$,
 - ② continue as with any false clause (learn an asserting clause, ...).
 - Check if there is an almost-cycle $n_1 \rightarrow n_2 \rightarrow \dots \rightarrow n_m \rightarrow n_1$ with all arcs *true* but one $a_{n_j, n_{j+1}}$. If so,
 - ① generate a clause $c = \neg a_{n_1, n_2} \vee \neg a_{n_2, n_3} \vee \dots \vee \neg a_{n_m, n_1}$,
 - ② add it to the clause database,
 - ③ add $\neg a_{n_j, n_{j+1}}$ to the propagation queue with c as its reason clause, and
 - ④ continue propagation.

Notice that there may be multiple such almost-cycles, each yielding a different literal.

- ① Run a SAT solver based on Conflict-Driven Clause Learning (CDCL).
- ② When an arc variable is assigned *true*,
 - Check whether the graph contains a cycle $n_1 \rightarrow n_2 \rightarrow \dots \rightarrow n_m \rightarrow n_1$. If it does,
 - ① generate a clause $\neg a_{n_1, n_2} \vee \neg a_{n_2, n_3} \vee \dots \vee \neg a_{n_m, n_1}$,
 - ② continue as with any false clause (learn an asserting clause, ...).
 - Check if there is an almost-cycle $n_1 \rightarrow n_2 \rightarrow \dots \rightarrow n_m \rightarrow n_1$ with all arcs *true* but one $a_{n_j, n_{j+1}}$. If so,
 - ① generate a clause $c = \neg a_{n_1, n_2} \vee \neg a_{n_2, n_3} \vee \dots \vee \neg a_{n_m, n_1}$,
 - ② add it to the clause database,
 - ③ add $\neg a_{n_j, n_{j+1}}$ to the propagation queue with c as its reason clause, and
 - ④ continue propagation.

Notice that there may be multiple such almost-cycles, each yielding a different literal.

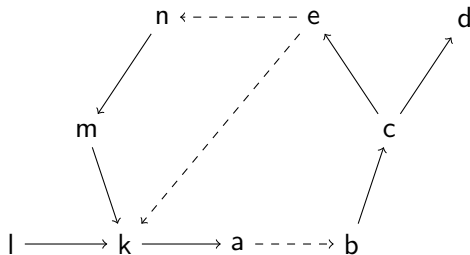
- ① Run a SAT solver based on Conflict-Driven Clause Learning (CDCL).
- ② When an arc variable is assigned *true*,
 - Check whether the graph contains a cycle $n_1 \rightarrow n_2 \rightarrow \dots \rightarrow n_m \rightarrow n_1$. If it does,
 - ① generate a clause $\neg a_{n_1, n_2} \vee \neg a_{n_2, n_3} \vee \dots \vee \neg a_{n_m, n_1}$,
 - ② continue as with any false clause (learn an asserting clause, ...).
 - Check if there is **an almost-cycle** $n_1 \rightarrow n_2 \rightarrow \dots \rightarrow n_m \rightarrow n_1$ with all arcs *true* but one $a_{n_j, n_{j+1}}$. If so,
 - ① generate a clause $c = \neg a_{n_1, n_2} \vee \neg a_{n_2, n_3} \vee \dots \vee \neg a_{n_m, n_1}$,
 - ② add it to the clause database,
 - ③ add $\neg a_{n_j, n_{j+1}}$ to the propagation queue with c as its reason clause, and
 - ④ continue propagation.

Notice that there may be multiple such almost-cycles, each yielding a different literal.

The Propagator

Example

Variable corresponding to $a \rightarrow b$ is made *true*.
Perform search **forward** from b (*true* arcs only).
Perform search **backward** from a (*true* arcs only).
Infer **negations** of arcs from **brown** to **purple**.
...deleting them.



The Propagator

Example

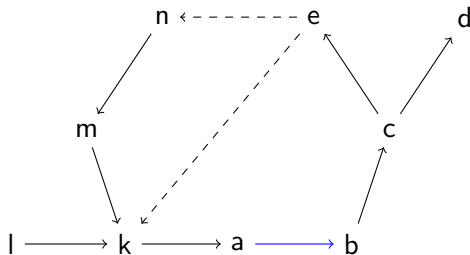
Variable corresponding to $a \rightarrow b$ is made *true*.

Perform search **forward** from b (*true arcs only*).

Perform search **backward** from a (*true arcs only*).

Infer **negations** of arcs from **brown** to **purple**.

...deleting them.



The Propagator

Example

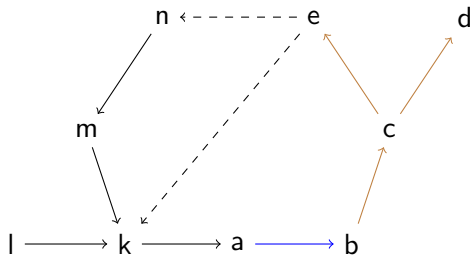
Variable corresponding to $a \rightarrow b$ is made *true*.

Perform search **forward** from b (*true* arcs only).

Perform search **backward** from a (*true* arcs only).

Infer **negations** of arcs from **brown** to **purple**.

...deleting them.



The Propagator

Example

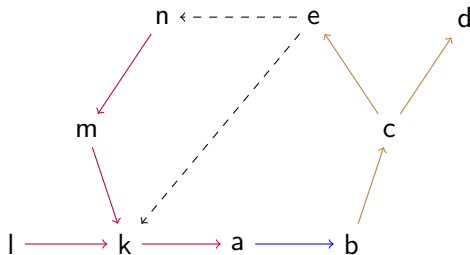
Variable corresponding to $a \rightarrow b$ is made *true*.

Perform search **forward** from b (*true arcs only*).

Perform search **backward** from a (*true arcs only*).

Infer **negations** of arcs from **brown** to **purple**.

...deleting them.



The Propagator

Example

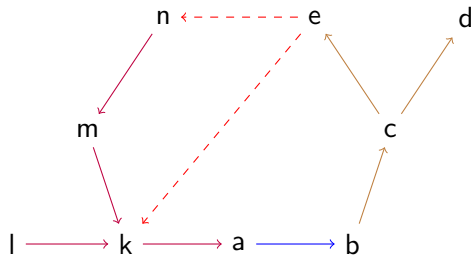
Variable corresponding to $a \rightarrow b$ is made *true*.

Perform search **forward** from b (*true* arcs only).

Perform search **backward** from a (*true* arcs only).

Infer **negations** of arcs from **brown** to **purple**.

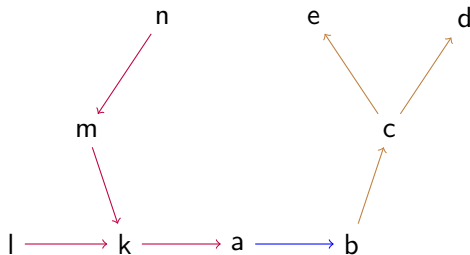
...deleting them.



The Propagator

Example

Variable corresponding to $a \rightarrow b$ is made *true*.
Perform search **forward** from b (*true* arcs only).
Perform search **backward** from a (*true* arcs only).
Infer **negations** of arcs from **brown** to **purple**.
...deleting them.



- embedding in MiniSAT and Glucose SAT solvers
- a couple of dozens of lines of C++
- Propagator run after every decision in CDCL.
- Runtime overhead typically ≤ 5 per cent, even for largish graphs (10000+ nodes).

Integration with CDCL **much simpler** than with typical SMT theories such as linear arithmetics.

Acyclicity as CNF Constraints

Enumerative encoding

For every $n_1 \rightarrow \dots \rightarrow n_m \rightarrow n_1$ have clause $\neg a_{n_1, n_2} \vee \dots \vee \neg a_{n_m, n_1}$.

Size: $\mathcal{O}(v^v)$

Transitive closure

$$a_{x,y} \rightarrow t_{x,y}$$

$$a_{x,y} \wedge t_{y,z} \rightarrow t_{x,z}$$

$$a_{x,y} \rightarrow \neg t_{y,x}$$

Size: $\mathcal{O}(ev)$

Acyclicity as CNF Constraints

Tree reduction

Assign each node inductively the maximum **distance** of the any of its children from a leaf. If all distances are finite, there is no cycle.

Size: $\mathcal{O}(ev)$

Topological sort

Every node $n \in N$ implies a binary number $i(n)$.

For every arc $(n, n') \in A$ have $a_{n,n'} \rightarrow (i(n) < i(n'))$.

Size: $\mathcal{O}(v \log v + e \log v)$

Acyclicity as CNF Constraints

Properties: detection of cycles, inferring forbidden arcs

INC	Is inconsistency (a cycle) detected with UP (Unit Propagation) after all arcs forming a cycle are enabled?
BACK	For an enabled path n_1, \dots, n_k , is arc (n_k, n_1) disabled by UP?

encoding	size	propagation
Enumerative	$\mathcal{O}(v^v)$	INC, BACK
Transitive Closure	$\mathcal{O}(ev)$	INC, BACK
Tree Reduction	$\mathcal{O}(ev)$	INC
Topological Sort	$\mathcal{O}(v \log v + e \log v)$	-

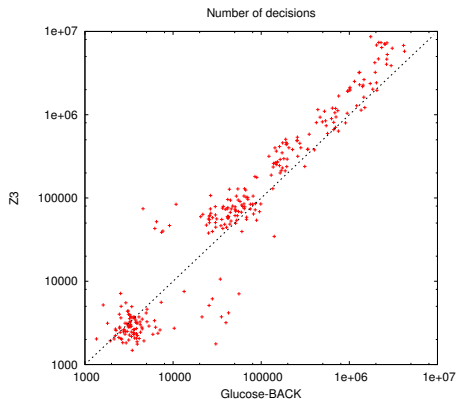
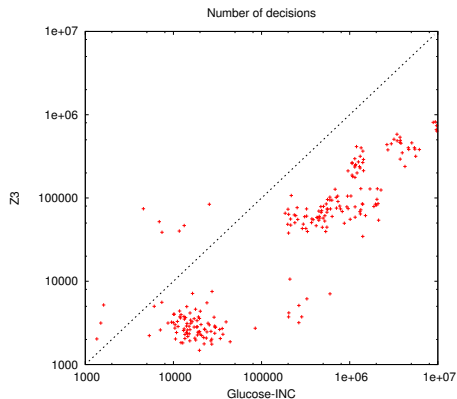
See also our paper in KR'14.

- Acyclicity can be easily encoded as the $<$ relation of integers/reals/rationals in SMT with linear real arithmetics and inequalities.
 - ① Numeric variable n for every node n .
 - ② For each arc variable $a_{n,n'}$ we have formula $a_{n,n'} \rightarrow (n < n')$.
- Some SMT solvers solve sets of simple inequalities like the above by **graph-based** algorithms, potentially detecting acyclicity efficiently and inferring forbidden arcs.
- However, in practice they are clearly outperformed by our SAT+acyclicity solver.

Runtime Comparison

Problem	Size	Glucose-INC	Glucose-BACK	MiniSAT-INC	MiniSAT-BACK	Glucose-SAT	MiniSAT-SAT	Lingeling-SAT	Clasp-SAT	Clasp-ASP	Z3-SMT
Hamilton	100	0.21	0.07	0.03	0.04	224.14	275.00	2419.63	2600.90	0.95	2.45
	150	0.13	0.15	0.10	0.12	3440.00	3172.54	3536.02	—	20.16	50.64
Acyclic	25	0.08	0.05	0.05	0.03	2406.60	2934.30	1.61	1282.49	0.12	0.29
	50	2.34	0.28	1.64	0.29	3147.91	2988.30	17.09	—	0.76	7.61
	75	682.86	8.09	856.47	4.76	3241.00	3276.92	99.60	—	282.01	167.74
	100	2180.98	964.28	2172.01	647.13	3170.48	3176.70	2760.52	1984.10	831.33	2278.63
Forest	25	0.59	0.64	0.75	0.72	118.70	139.88	3.10	3.59	4.09	4.54
	50	301.46	304.44	466.56	498.00	1165.53	1438.49	667.24	1125.86	1039.26	1205.63
	75	909.15	1006.73	1011.05	920.43	2597.99	2708.27	1019.68	1470.12	1501.76	1755.28
	100	1349.29	1418.25	1271.86	1269.47	2882.20	2853.03	2131.73	2597.71	1632.94	2690.67
Tree	25	0.80	0.74	0.67	0.83	72.93	6.12	3.17	4.12	4.37	4.75
	50	301.81	315.83	564.05	544.43	815.09	1230.09	685.38	1126.76	1193.09	1208.36
	75	947.61	999.07	976.40	1025.02	2646.64	2749.26	1044.51	1633.95	1495.32	1726.56
	100	1348.91	1414.68	1330.81	1224.28	2882.36	2861.33	2239.12	2621.82	1995.19	2538.20

Explaining Performance of SMT / Difference Logic Solvers



- Graph properties important in many applications:
 - **s-t-reachability**: node t reachable from s (directed, undirected)
 - **simple paths**: a node is on a simple path between s and t
 - **cycles**: acyclicity, cyclicity
 - **chordality**: graph consists of triangles
- Devising efficient (linear-time) propagators often a challenge. (\rightsquigarrow Explains why compact and efficient CNF-encodings hard to come by.)

- Proposed a framework SAT modulo Graphs.
- Presented efficient and simple implementation of SAT + Acyclicity.

- Future work: implementation MAXSAT modulo Graphs
- Future work: other graph properties
- Future work: applications SAT + Graphs
- Remaining performance differences to ASP solvers such as Clasp?