

# Dinosat: A SAT Solver with Native DNF Support

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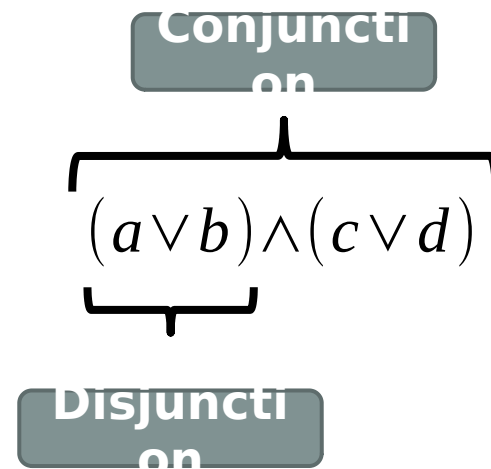


- CAS Merlin: SAT-based Product Configuration
- Not CNF: also AMO and DNF subformulas
- Slightly different problem: online algorithm produces optimal solutions

# This Work

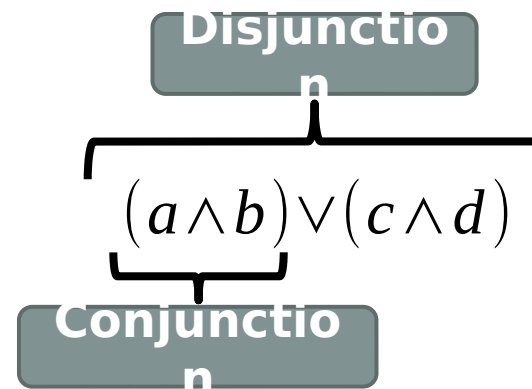
- Introduce format RichCNF (Clauses + DNF and AMO constraints)
- Write DPLL solver which also propagates DNF and AMO
- Write CDCL solver which learns from conflicts with DNF and AMO
- Evaluate Phase Transitions: SAT/UNSAT, Performance

- Modern SAT solvers solve formulas in their „conjunctive normal form“ (CNF) [1]



# Other constraint types

- The „disjunctive normal form“ (DNF) is a disjunction of conjunctions



- The „At most one constraint“ (AMO) only allows at most one literal to be true

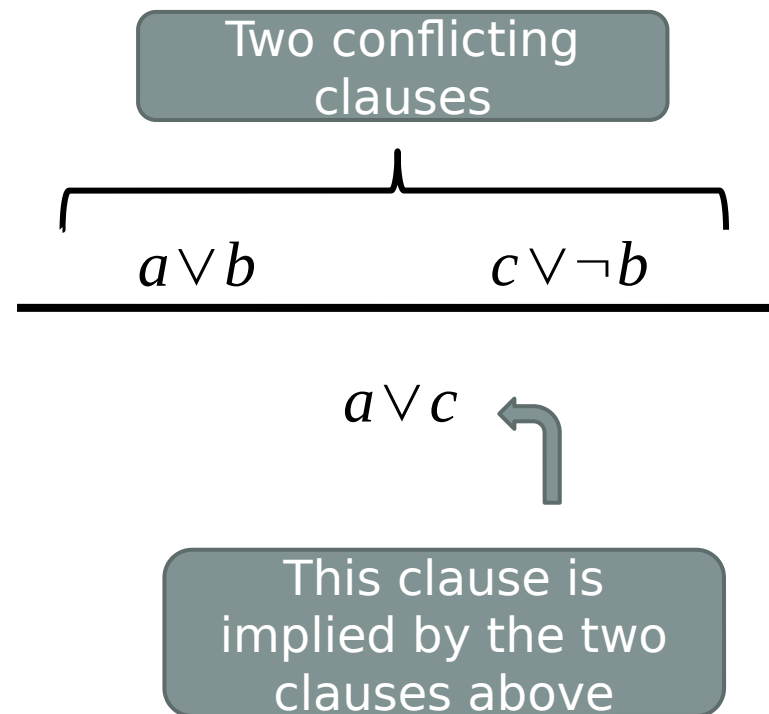
$$AMO(a, b, c, d)$$

# Two major SAT solving algorithms [1]

- Davis-Putnam-Logemann-Loveland (DPLL) algorithm
  - Exhaustive depth-first search of the space of variable assignments
  - Resolves conflict, by trying another value
- Conflict-Driven-Clause-Learning (CDCL) algorithm
  - Evolved from the DPLL-algorithm
  - Resolves conflict by learning new clauses

# Resolution [2]

- The current best SAT solvers use a concept called „resolution“



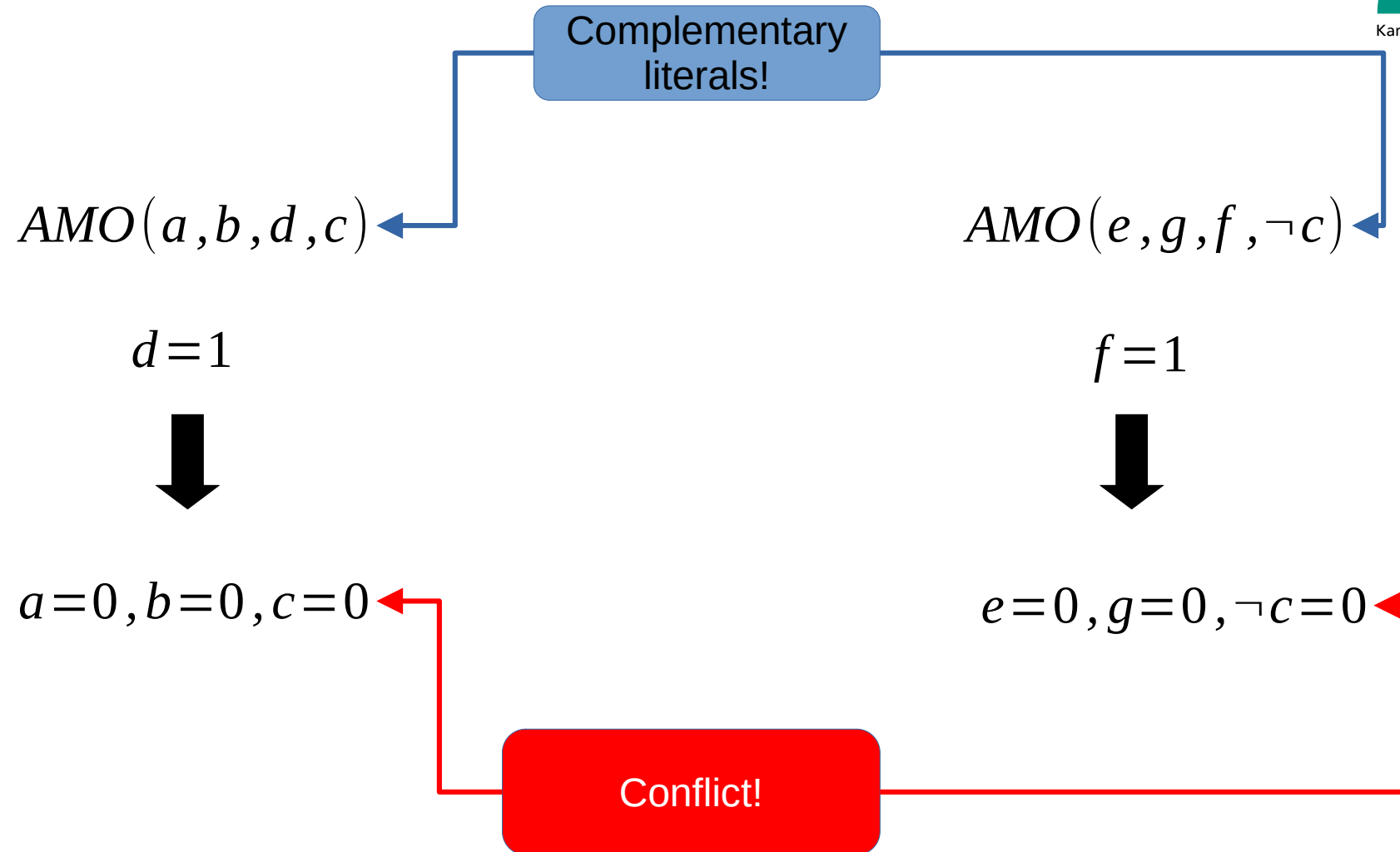
# Notation in the next slides

- The next slides use the following notation for DNF constraints:

$$(a \wedge b) \vee (c \wedge d) \Leftrightarrow DNF((a, b), (c, d))$$



# First AMO-AMO conflict



# First AMO-AMO conflict

$$AMO(a, b, d, c) \quad AMO(e, g, f, \neg c)$$

---

$$(\neg a \wedge \neg b \wedge \neg d) \vee (\neg e \wedge \neg g \wedge \neg f)$$

Not a CNF at the moment!

# First AMO-AMO conflict

$$(\neg a \wedge \neg b \wedge \neg d) \vee (\neg e \wedge \neg g \wedge \neg f)$$



$$\begin{aligned} &(\neg a \vee \neg e) \wedge (\neg a \vee \neg g) \wedge (\neg a \vee \neg f) \wedge \\ &(\neg b \vee \neg e) \wedge (\neg b \vee \neg g) \wedge (\neg b \vee \neg f) \wedge \\ &(\neg d \vee \neg e) \wedge (\neg d \vee \neg g) \wedge (\neg d \vee \neg f) \end{aligned}$$

**Lemma 4.2.1.** *Consider two AMO constraints  $AMO_1$  and  $AMO_2$ . Both constraints are complementary on the variable  $x_a$ .  $AMO_1$  contains exactly one literal  $x_a$  with  $AMO_2$  containing the complementary literal  $\neg x_a$ . Let  $\{y_1, \dots, y_k\}$  be the set of literals of  $AMO_1$  without  $x_a$  and  $\{z_1, \dots, z_m\}$  be the set of literals of  $AMO_2$  without  $\neg x_a$ . If a conflict occurs between these constraints, then it can be resolved by learning the following clauses:*

$$\{\neg y_i \vee \neg z_j \mid y_i \in \{y_1, \dots, y_k\}, z_j \in \{z_1, \dots, z_m\}, \{y_i, z_j\} \notin \{x_a, \neg x_a\}\}$$

# First AMO-AMO conflict

$$(\neg a \wedge \neg b \wedge \neg d) \vee (\neg e \wedge \neg g \wedge \neg f)$$



Too many clauses?

$$\begin{aligned} &(\neg a \vee \neg e) \wedge (\neg a \vee \neg g) \wedge (\neg a \vee \neg f) \wedge \\ &(\neg b \vee \neg e) \wedge (\neg b \vee \neg g) \wedge (\neg b \vee \neg f) \wedge \\ &(\neg d \vee \neg e) \wedge (\neg d \vee \neg g) \wedge (\neg d \vee \neg f) \end{aligned}$$

# First AMO-AMO conflict

$$AMO(a, b, d, c)$$

$$d=1$$



$$a=0, b=0, c=0$$

$$AMO(e, g, f, \neg c)$$

$$f=1$$



$$e=0, g=0, \neg c=0$$

# First AMO-AMO conflict

$$AMO(a, b, d, c) \quad AMO(e, g, f, \neg c)$$

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$$(\neg d \vee \neg f)$$

$$d=1, f=1$$

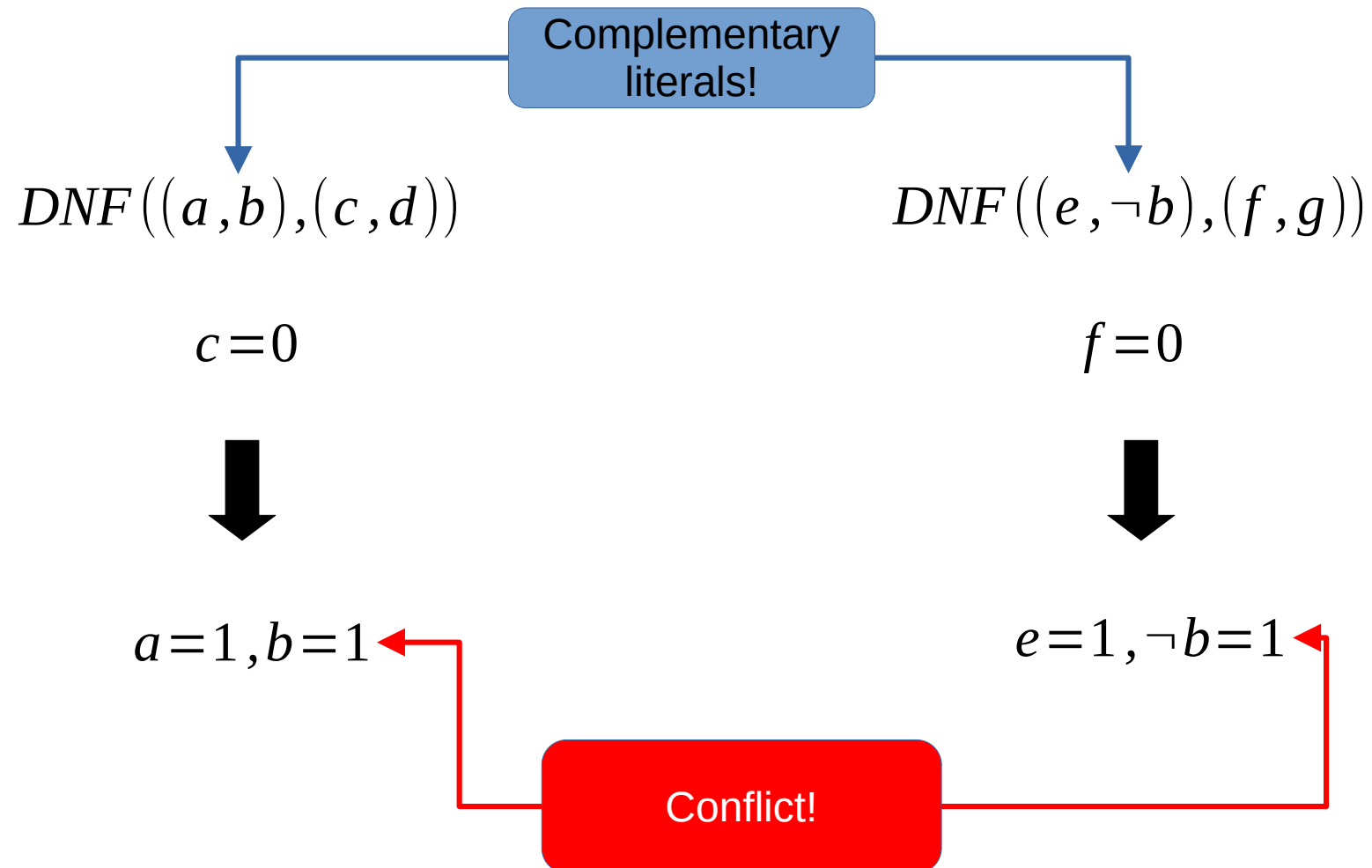
# First AMO-AMO conflict

**Lemma 4.2.2.** *Consider two AMO constraints  $AMO_1$  and  $AMO_2$ . Both constraints are complementary on the variable  $x_a$ .  $AMO_1$  contains exactly one literal  $x_a$  with  $AMO_2$  containing the complementary literal  $\neg x_a$ . Let  $y_i$  be a literal that is true in  $AMO_1$  and not  $x_a$ . Let  $z_j$  be a literal that is true in  $AMO_2$  and not  $\neg x_a$ . Then this specific conflict can be avoided by learning the following clause:*

$$\neg y_i \vee \neg z_j$$



# DNF-DNF conflict



# DNF-DNF conflict

$$DNF((a,b),(c,d)) \quad DNF((e,\neg b),(f,g))$$

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$$DNF((c,d),(f,g))$$

**Lemma 4.3.1.** *Consider two DNF constraints  $DNF_1$  and  $DNF_2$ , that are complementary on the variable  $x$ .  $DNF_1$  contains the literal  $x$  and  $DNF_2$  contains the literal  $\neg x$ . A conflict, that is caused by the variable  $x$ , can then be resolved by learning the following constraints:*

$$DNF_1/x \vee DNF_2/\neg x$$

# DNF-DNF conflict

$$DNF((c, d), (f, g))$$



$$(c \vee f) \wedge (c \vee g) \wedge (d \vee f) \wedge (d \vee g)$$

Every learnt DNF is  
effectively a large  
amount of clauses

# DNF-DNF conflict

$$DNF((a, b), (c, d))$$

$$c = 0$$



$$a = 1, b = 1$$

$$DNF((e, \neg b), (f, g))$$

$$f = 0$$



$$e = 1, \neg b = 1$$

# DNF-DNF conflict

$$DNF((a, b), (c, d)) \quad DNF((e, \neg b), (f, g))$$

---

Significantly fewer  
constraints


$$c \vee f$$

$$c=0, f=0$$

**Lemma 4.3.2.** *Consider two DNF constraints  $DNF_1$  and  $DNF_2$  and the variable  $x$ , that the two constraints are complementary on.  $DNF_1$  contains the literal  $x$  and  $DNF_2$  contains the literal  $\neg x$ . Let  $\{y_1, \dots, y_n\}$  be the literals of  $DNF_1$ , that turned false and therefore forced a unit propagation of the literal  $x$ . Let  $\{z_1, \dots, z_m\}$  be the literals of  $DNF_2$ , that turned false and therefore caused the propagation of the literal  $\neg x$ . Then this specific conflict can be resolved by learning the following clause:*

$$y_1 \vee \dots \vee y_n \vee z_1 \vee \dots \vee z_m$$

# Phase transition [3]

- Phase transition point is the clause to variable ratio, where about 50 percent of the randomly generated formulas are unsatisfiable
- At the phase transition point of the clauses, there are difficult instances
- Does there exist a phase transition point for the other constraint types?



# Phase transition

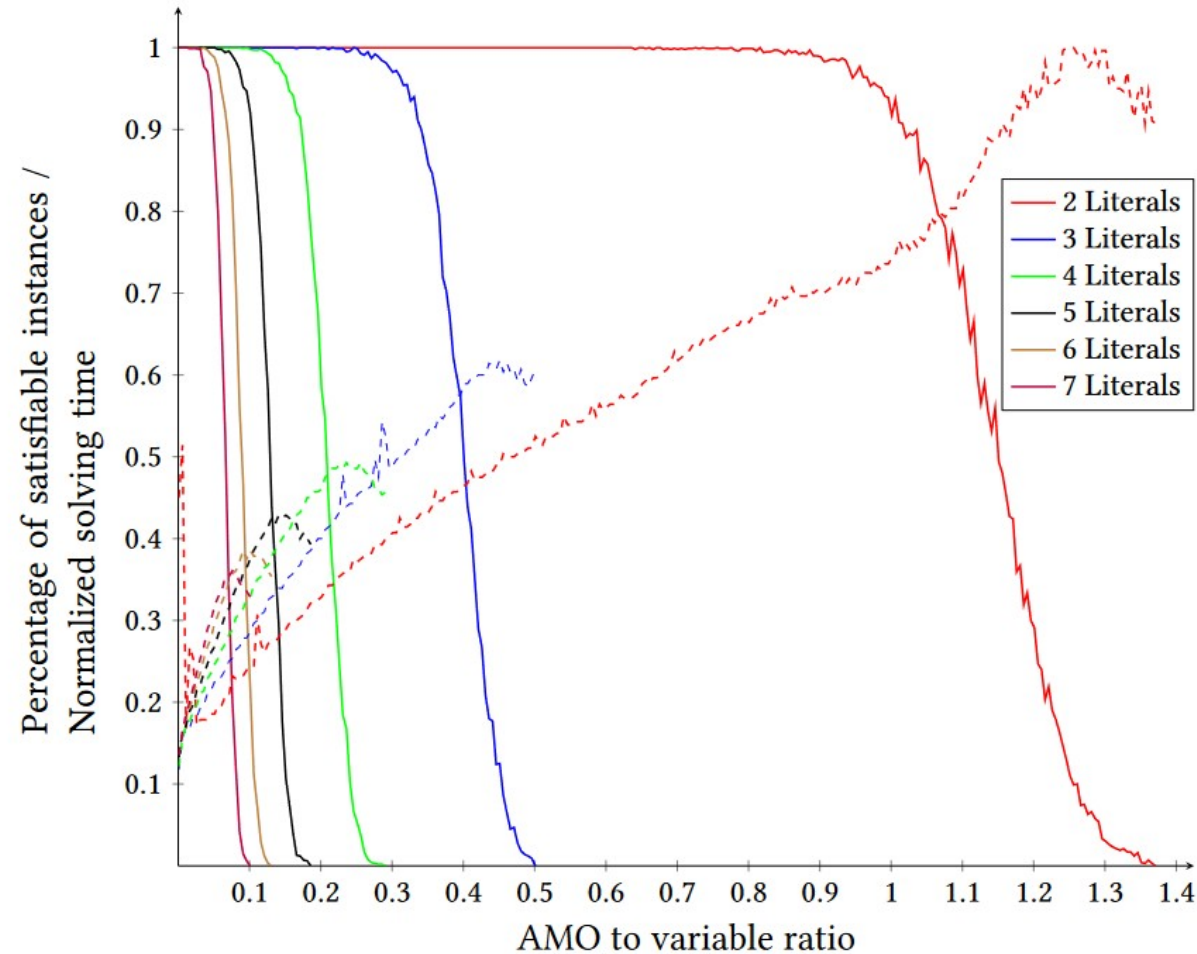


Figure 6.1: Phase transition of AMO constraints with 1000 variables and an increment of five AMO constraints per iteration

# Phase transition

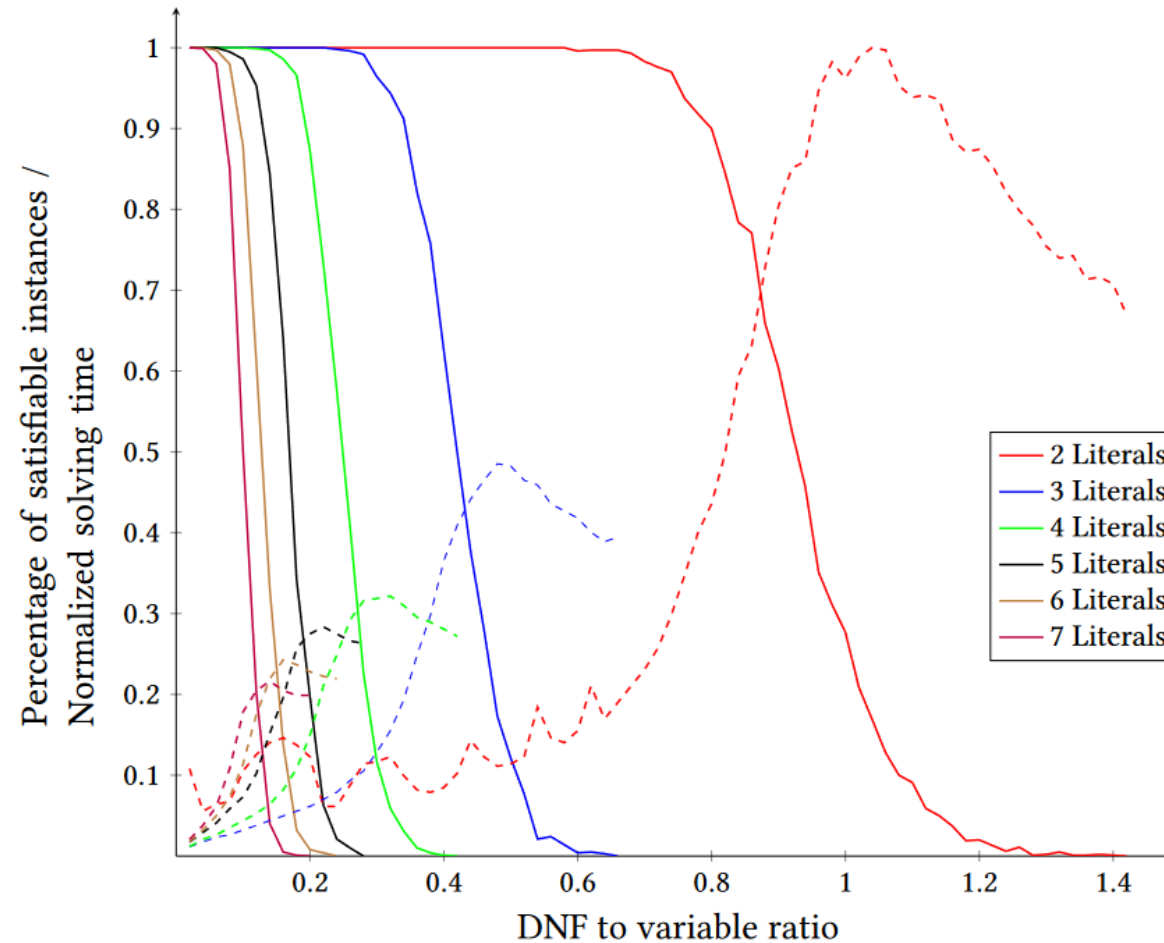


Figure 6.2: Phase transition and solving time of DNF constraints with a constant term count of 3, 50 variables, and a DNF increment of 1 per iteration

# Phase transition

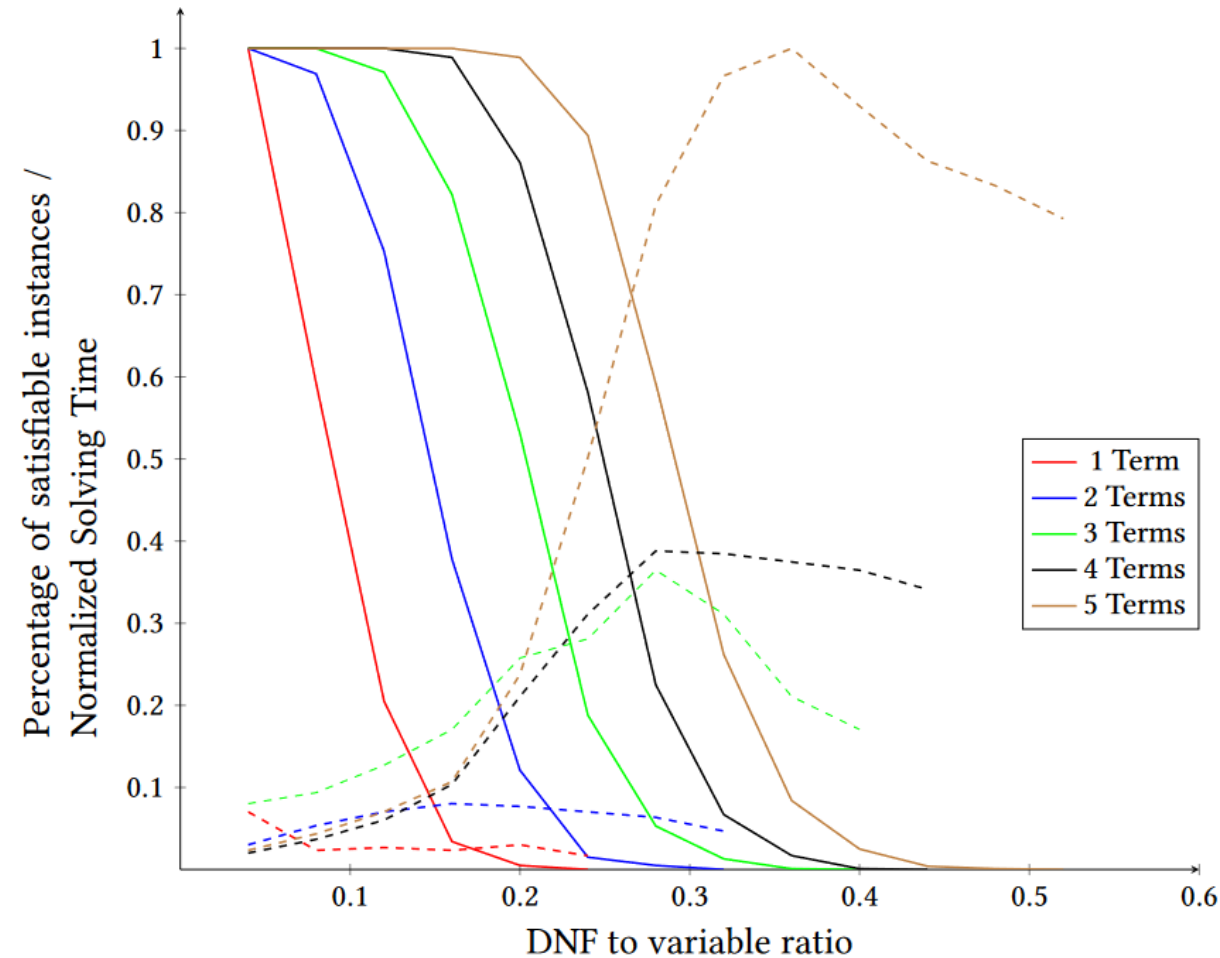


Figure 6.3: Phase transition and solving time of DNF constraints with a constant term length of 5, 25 variables and a DNF increment of 1 per iteration

# Evaluation

- Industrial benchmarks provided by CAS
- Randomized benchmarks
- Performance comparison with Sat4j
- Encoding of benchmarks, so that Sat4j can solve them

# Industrial benchmarks

Table 6.1: Composition of the industrial benchmark sets with the number of Formulas (F), the average number of variables (V), the average number of DNF constraints (DNF), the average number of terms per DNF (TPD), average number of literals per term (LPT), the average number of clauses (C), the average number of literals per clause (LPC), the average number of AMO constraints (AMO) and the average number of literals per AMO constraint (LPA)

Name	F	V	DNF	TPD	LPT	C	LPC	AMO	LPA
$Ind_{large}$	20	27815.40	2645.55	7.50	32.38	114661.60	11.63	917.30	16.25
$Ind_{medium}$	21	13795.14	546.52	3.98	9.67	18504.38	5.87	393.00	12.40
$Ind_{small}$	26	6949.23	155.96	2.72	5.42	8626.42	4.02	134.19	16.00
$(CNF)Ind_{large}$	20	49742.00	0.00	0.00	0.00	797924.50	4.18	0.00	0.00
$(CNF)Ind_{medium}$	21	19329.38	0.00	0.00	0.00	53697.86	3.71	0.00	0.00
$(CNF)Ind_{small}$	26	9057.96	0.00	0.00	0.00	16935.81	3.15	0.00	0.00

Table 6.2:  $Ind_{large}$  and  $(CNF)Ind_{large}$  performance evaluation with the solving time (ST), number of solved instances (SI), number of timeouts (TO), average number of branching decisions (D(A)), average number of unit propagations (P(A)) and the average number of conflicts (C(A))

Solver	ST	SI	TO	D(A)	P(A)	C(A)
$DPLL_{NR\_F}$	12.144	20	0	26318.40	9797.55	510.10
$DPLL_{R\_F}$	10.668	20	0	35914.35	15574.10	656.30
$CDCL_{R\_F}$	42.942	20	0	671542.00	945384.80	9085.85
$CDCL_{R\_F\_CNF}$	99.89	20	0	1030202.95	4973969.20	2583.40
$Sat4j$	18.867	20	0	82588.10	726588.50	48.25

Table 6.3:  $Ind_{medium}$  and  $(CNF)Ind_{medium}$  performance evaluation with the solving time (ST), number of solved instances (SI), number of timeouts (TO), average number of branching decisions (D(A)), average number of unit propagations (P(A)) and the average number of conflicts (C(A))

Solver	ST	SI	TO	D(A)	P(A)	C(A)
$DPLL_{NR\_F}$	2.558	21	0	11403.43	2391.71	0.00
$DPLL_{R\_F}$	1.849	21	0	11403.43	2391.71	0.00
$CDCL_{R\_F}$	1.576	21	0	11403.43	2391.71	0.00
$CDCL_{R\_F\_CNF}$	2.086	21	0	10888.57	10895.29	1.76
$Sat4j$	1.579	21	0	6822.62	16236.81	0.00



Table 6.4:  $Ind_{small}$  and  $(CNF)Ind_{small}$  performance evaluation with the solving time (ST), number of solved instances (SI), number of timeouts (TO), average number of branching decisions (D(A)), average number of unit propagations (P(A)) and the average number of conflicts (C(A))

Solver	ST	SI	TO	D(A)	P(A)	C(A)
$DPLL_{NR\_F}$	1.799	26	0	5712.42	1245.27	2.15
$DPLL_{R\_F}$	0.876	26	0	5712.42	1245.27	2.15
$CDCL_{R\_F}$	1.011	26	0	6012.42	1895.88	4.08
$CDCL_{R\_F\_CNF}$	0.958	26	0	5485.58	6132.15	3.15
$Sat4j$	0.914	26	0	3900.38	8410.46	0.85



# Randomized benchmarks

Table 3: DNF constraints with 15 terms each with 3 literals, performance evaluation with the solving time (ST), number of solved instances (SI), number of timeouts (TO), average number of branching decisions (D(A)), average number of unit propagations (P(A)) and the average number of conflicts (C(A))

Solver	ST	SI	TO	D(A)	P(A)	C(A)
Satisfiable Benchmark Set						
$DPLL_{NR\_F}$	169.861	99	0	29979.13	83177.88	29969.36
$DPLL_{R\_F}$	1495.094	99	0	265148.13	730542.03	263769.10
$CDCL_{R\_F}$	6019.026	70	29	348181.73	718620.80	270602.02
$CDCL_{R\_F\_CNF}$	10873.713	18	81	400048.77	46125526.05	119606.17
SAT4J	355.249	99	0	24897.67	6970444.00	22712.35
Unsatisfiable Benchmark Set						
$DPLL_{NR\_F}$	371.622	101	0	69360.25	192030.95	69361.25
$DPLL_{R\_F}$	5170.768	101	0	951018.38	2620153.44	946667.61
$CDCL_{R\_F}$	12120.204	0	101	691474.96	1439292.20	536616.08
$CDCL_{R\_F\_CNF}$	12120.63	0	101	479496.85	55210042.55	143715.06
SAT4J	802.786	101	0	51116.41	14393933.36	47212.17

# Conclusions and future work

- The new solver was able to outperform Sat4j in specific benchmarks
- The other constraints aren't always beneficial
- Sat4j generally has significantly less branching decisions
  - Has a major impact on the solving time
- Sat4j is faster in pure CNF solving
  - An improvement in this area might lead to faster solving times for the new constraint types