

Difference Logic

Satisfiability Checking Seminar

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Abstract

This report describes the difference logic (DL) and a graph-based approach for solving satisfiability (SAT) problem of DL formulas. There is of course a simplex-based algorithm which solves SAT problem of any linear arithmetic (LA) constraints. However, it is not efficient compared to the algorithm described here because simplex does not utilize the simple structure of DL constraints.

Efficiently solving SAT problem of DL constraints is very important because a lot of timing related problems can be described by this logic e.g. scheduling problems, detecting race conditions in digital circuits etc.

The report is organized as follows. Chapter 1 introduces difference logic. Chapter 2 gives theoretical background on SAT checking. Chapter 3 describes a graph-based approach to solving SAT problem of DL. Chapter 4 draws a conclusion.

1 Introduction

1.1 Difference Logic

DL is a special case of an LA logic. [1] and [2, p.5] define DL as follows:

Definition 1.1 (Difference Logic) *Let $\mathcal{B} = \{b_1, b_2, \dots\}$ be a set of Boolean variables and $\mathcal{X} = \{x_1, x_2, \dots\}$ be a set of numerical variables over a domain \mathbb{D} . The domain \mathbb{D} is either the Integers \mathbb{Z} or the Reals \mathbb{R} . The difference logic over \mathcal{B} and \mathcal{X} is called $DL(\mathcal{X}, \mathcal{B})$ and given by the following grammar:*

$$\phi \stackrel{\text{def}}{=} b \mid (x - y \prec c) \mid \neg\phi \mid \phi \wedge \phi$$

where $b \in \mathcal{B}$, $x, y \in \mathcal{X}$, $c \in \mathbb{D}$ is a constant and $\prec \in \{<, \leq\}$ is a comparison operator.

The remaining Boolean connectives $\vee, \rightarrow, \leftrightarrow, \dots$ can be defined in the usual ways in terms of conjunction \wedge and negation \neg .

Examples of DL formulas are given below:

$$\phi_1 = (p \vee q \vee r) \wedge (p \rightarrow (u - v < 3)) \wedge (q \rightarrow (v - w < -5)) \wedge (r \rightarrow (w - x < 0)) \quad (1)$$

$$\phi_2 = (u - v < 1) \wedge (v - w < 5) \wedge (w - x \leq -3) \wedge (x - y < 1) \wedge (y - z \leq -5) \wedge (y - v \leq 0) \quad (2)$$

$$\phi_3 = (u - v < 1) \wedge (v - w < 5) \wedge (w - x \leq -3) \wedge (x - y < -3) \wedge (y - z \leq -5) \wedge (y - w < 4) \quad (3)$$

2 Preliminaries

2.1 Solving SAT Problem of Propositional Logic

Most of the SAT solvers employ a variation of the Davis-Putnam-Logemann-Loveland (DPLL) algorithm [3, 4] for solving SAT problem of the propositional logic (PL). One such basic SAT checking algorithm is given below:

Algorithm 1 A basic SAT checking algorithm for solving SAT problem of PL. It takes a PL formula to be checked for SAT and returns SAT status of the formula (SAT or UNSAT). It also returns a model i.e. an assignment, which evaluates the formula to *True*, in case if the formula is SAT.

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CHECK( PL formula  $\phi$ )
1   $model \leftarrow \emptyset$ 
2   $(inferredAssignments, conflictingClauses) \leftarrow \text{PROPAGATE}(\phi, model)$ 
3   $conflictHasArisen \leftarrow conflictingClauses \neq \emptyset$ 
4  if  $conflictHasArisen$ 
5    then return (UNSAT, NIL)
6   $model \leftarrow model \cup inferredAssignments$ 
7  while True
8    do  $(nextVariable, value) \leftarrow \text{DECIDE}(\phi, model)$ 
9       $allVariablesHaveAlreadyBeenAssigned \leftarrow nextVariable = \text{NIL}$ 
10     if  $allVariablesHaveAlreadyBeenAssigned$ 
11       then return (SAT,  $model$ )
12      $model \leftarrow model \cup \{nextVariable \leftarrow value\}$ 
13     repeat
14        $(inferredAssignments, conflictingClauses) \leftarrow \text{PROPAGATE}(\phi, model)$ 
15        $model \leftarrow model \cup inferredAssignments$ 
16        $conflictHasArisen \leftarrow conflictingClauses \neq \emptyset$ 
17       if  $conflictHasArisen$ 
18         then  $(newModelWithoutConflict, \phi_a) \leftarrow \text{RESOLVE}(\phi, model, conflictingClauses)$ 
19            $conflictHasNotBeenResolved \leftarrow newModelWithoutConflict = \text{NIL}$ 
20           if  $conflictHasNotBeenResolved$ 
21             then return (UNSAT, NIL)
22            $model \leftarrow newModelWithoutConflict$ 
23            $\phi \leftarrow \phi \wedge \phi_a$ 
24     until  $\neg conflictHasArisen$ 

```

The Algorithm 1 is quite generic. It is more of a template. One needs to plug into this template his own implementations of the following functions:

PROPAGATE This function calculates all assignments that follow from a given PL formula and a given model. It also returns a list of conflicting clauses (if there are any). These clauses will be in conflict if one extends the model by the returned assignments.

DECIDE This function applies some heuristic and selects a variable to be set next and a value.

RESOLVE This function resolves a conflict or returns NIL if it cannot be resolved.

In the Algorithm 1 a model is represented by a mapping from PL variables of the input PL formula to Booleans. It is a simplification. Real-world SAT solvers maintain a lot of

additional information such as decision levels, assignment order of variables for every decision level, an implicant for every variable (i.e. the clause from which the variable's value was inferred during the PROPAGATE) etc.

Additionally, a care should be taken when resolving a conflict and computing a new model. The solver should make sure it visits each state associated with a model once only.

2.2 Solving SAT Problem of Difference Logic

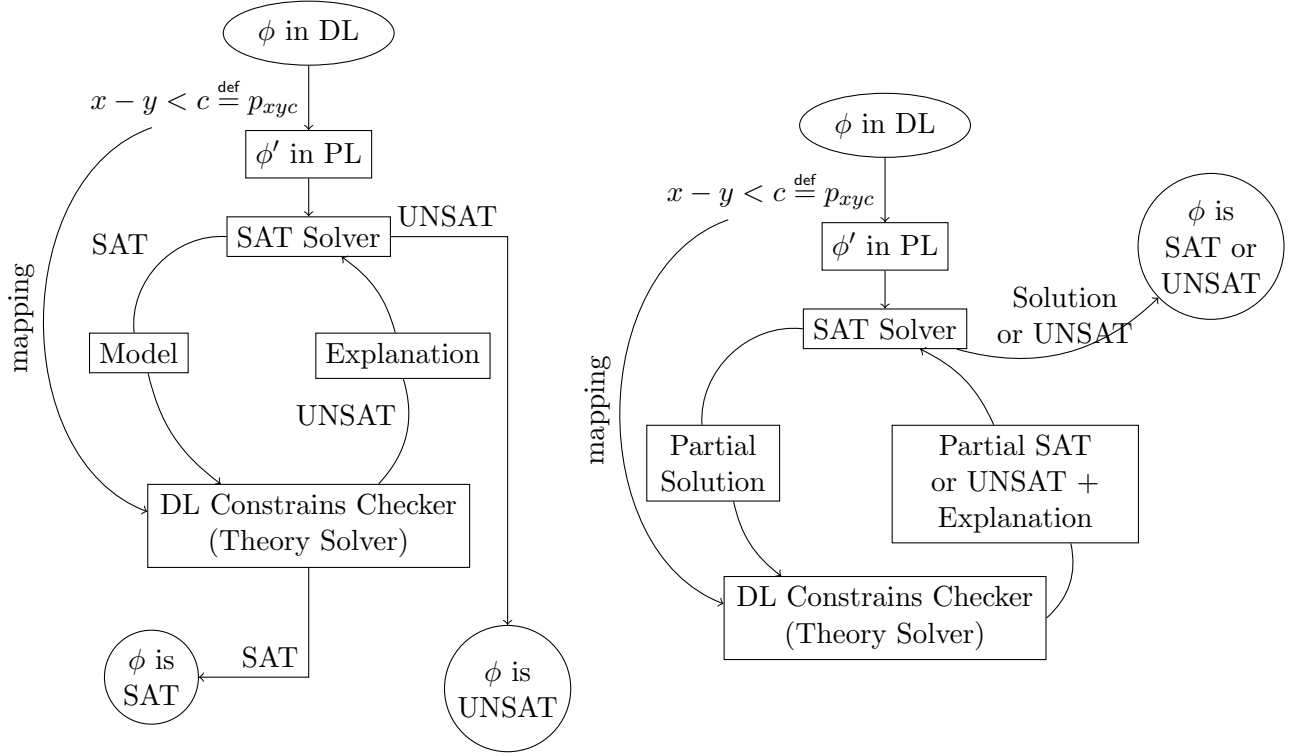


Figure 1: Illustration of the lazy (left) and incremental (right) approaches.

[1] mentions the following main approaches for solving the SAT problem of DL:

- Preprocessing approach. This approach suggests transforming a DL formula into an equivalent PL formula by encoding all intrinsic dependencies between DL constraints in PL. An example of such a dependency could be transitivity:

$$(x - y < a) \wedge (y - z < b) \rightarrow (x - z < a + b) \quad (4)$$

After the transformation a SAT solver can be used to check SAT of the resulting equivalent PL formula. If the PL formula is SAT then the solution for the original DL formula can be constructed by the reverse transformation.

- Lazy approach (Figure 1 left). This approach suggests substituting each DL constraint $x - y < c$ with a Boolean variable $p_{xyz} \in \mathbb{B}$ thus yielding a PL formula ϕ' . ϕ' represents the "skeleton", the Boolean abstraction over the original DL formula ϕ . Then a SAT solver is used in tandem with a DL constraints checker (the theory solver) to solve the SAT problem. In this approach the SAT solver always computes a complete solution which is then passed to the theory solver.

- Incremental approach (Figure 1 right). This approach is very similar to the lazy one. However, instead of computing a complete solution, the SAT solver invokes the DL constraints checker each time it updates its model. The DL constraints checker should be able to maintain some internal state of the currently received DL constraints and update it incrementally (i.e. add new constraints, delete existing ones). Hence the name of the approach.

3 Topic

3.1 Notation

Throughout this Chapter the following notation is used:

- ϕ is a conjunction of DL constraints. It is being checked for SAT.
- $x - y \prec c$ is a general form of a DL constraint in ϕ where $\prec \in \{<, \leq\}$.
- \mathbb{D} is a domain over which the variables and constants in ϕ are defined (e.g. \mathbb{R}).

3.2 Constraint Graph

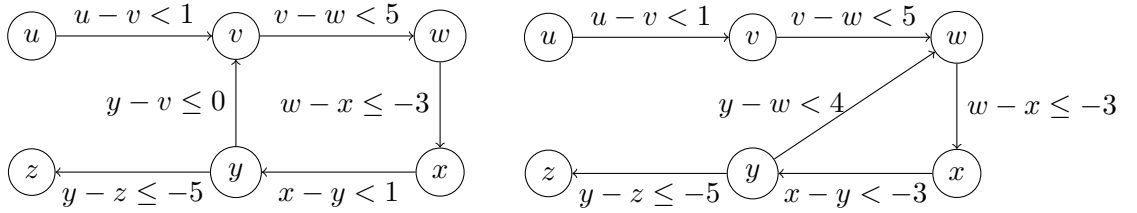


Figure 2: Examples of constraint graphs for Equation 2 (left) and Equation 3 (right).

Constraint graph (Figure 2) is a weighted directed graph which represents ϕ and which is used by a DL constraints checker (Figure 1) to test if ϕ is SAT. In [1] it is defined as follows:

Definition 3.1 (Constraint Graph) *The constraint graph is a graph $\Gamma = (V, E, weight, op)$ where:*

- V is a set of vertices. Each vertex $x \in V$ corresponds to one numeric variable occurring in $x - y \prec c$.
- E is a set of directed edges. Each edge $(x, y) \in E$ corresponds to $x - y \prec c$.
- $weight : E \mapsto \mathbb{D}$ is a weight function. It maps each edge $(x, y) \in E$ to the constant $c \in \mathbb{D}$ from the corresponding DL inequality $x - y \prec c$.
- $op : E \mapsto \{<, \leq\}$ is a function which maps each edge $(x, y) \in E$ to the operation \prec from the corresponding DL inequality $x - y \prec c$.

3.3 Negative Cycles in Constraint Graph

There is a direct correspondence between a negative cycle in a constraint graph and SAT of ϕ represented by this graph.

A path in the graph corresponds to a sum of the corresponding constraints. E.g. the path $u \rightarrow v \rightarrow w \rightarrow x$ in the left graph on Figure 2 corresponds to the following sum of the DL inequalities:

$$\begin{array}{rcl} u - v & < & 1 \\ v - w & < & 5 \\ w - x & \leq & -3 \\ \hline u - x & < & 3 \end{array} \quad (5)$$

If at least one strict inequality is present then the resulting inequality will also be strict. This summation along a path can also be expressed with an inferred transitivity constraint (e.g. Equation 4). The transitivity constraint naturally follows from ϕ and therefore must be satisfied in order to satisfy ϕ .

A cycle in the constraint graph corresponds to an inequality $0 \prec c$ which may cause a conflict in the following situations:

- $c < 0$
- $c = 0$ and \prec is $<$ (can be checked with *op* from Definition 3.1)

An example of a conflict can be seen on the right graph on Figure 2. The conflict corresponds to the negative cycle $x \rightarrow y \rightarrow w \rightarrow x$ which corresponds to the following conflicting inequalities:

$$\begin{array}{rcl} x - y & < & -3 \\ y - w & < & 4 \\ w - x & \leq & -3 \\ \hline 0 & < & -2 \end{array} \quad (6)$$

3.4 Bellman-Ford Algorithm for Constraint Graph

[1] uses a Goldberg-Radzik [6] variant of the Bellman-Ford algorithm (Algorithm 2) to detect negative cycles. [6] states that the algorithm has the same worst-case complexity $O(|V| \cdot |E|)$ as Bellman-Ford algorithm but is superior in practice. Important terminology and notation used in the algorithm are given below:

- The source vertex $s \in V$ is a vertex from which the shortest paths to other vertices are computed.
- $d(v) \in \mathbb{D}$ is a distance estimate from the source vertex to the given vertex $v \in V$.
- $r_d(x, y) = \text{weight}(x, y) + d(x) - d(y)$ is the reduced cost function [6]. It shows if it is possible to improve the distance estimate $d(y)$ by taking a path through the intermediate vertex $x \in V$.
- $\text{status}(v) = \{\text{unreached}, \text{labeled}, \text{scanned}\}$ is a status of a vertex $v \in V$. $\text{status}(v) = \text{unreached}$ means v has not been explored yet. $\text{status}(v) = \text{labeled}$ means v has been explored i.e. the distance estimate for it has been updated at least once and potentially it can be used to improve distance estimates to other vertices. $\text{status}(v) = \text{scanned}$ means v has been completely explored and will not be considered further for improving distance estimates.

- Edge $(x, y) \in E$ is called admissible if $r_d(x, y) < 0$ i.e. this edge can improve the current distance estimate for the vertex $y \in V$.
- Admissible graph Γ_d is a subgraph of Γ composed of the admissible edges of Γ . It is dynamic because it depends on the distance estimates which may change at each iteration of the Algorithm 2.

Algorithm 2 An algorithm for checking if ϕ which corresponds to the input constraint graph $\Gamma = (V, E, weight, op)$ is SAT. It returns SAT or UNSAT status and a set of DL constraints corresponding to a conflict (in case of UNSAT). It is based on Bellman-Ford algorithm [5, p.561]. Goldberg-Radzik heuristic [6], which is used here, suggests to scan a graph in a topological order. This algorithm uses depth first search [5, p.603] (DFS) and breadth first search [5, p.594] (BFS) for auxiliary tasks.

GOLDBERG-RADZIK(constraint graph $\Gamma = (V, E, weight, op)$, source vertex $s \in V$)

```

1  for each vertex  $x \in V$ 
2  do  $d(x) = \infty$ 
3       $status(x) = unreached$ 
4   $d(s) = 0$ 
5   $status(s) = labeled$ 
6   $A \leftarrow \emptyset$ 
7   $B \leftarrow \{s\}$ 
8  repeat
9      if  $\Gamma_d$  has a cycle (DFS on  $\Gamma_d$  can be used to check it)
10     then return (UNSAT, DL constraints corresponding to the detected cycle )
11     for each vertex  $x \in B$ 
12     do if  $x$  has no outgoing admissible edges
13         then  $B \leftarrow B \setminus \{x\}$ 
14          $status(x) = scanned$ 
15      $A \leftarrow$  set of unexplored vertices reachable from  $B$  in  $\Gamma_d$  (BFS on  $\Gamma_d$  can be used here)
16      $A \leftarrow$  sort  $A$  topologically using  $\Gamma_d$  as an input graph (DFS on  $\Gamma_d$  can be used here)
17      $B \leftarrow \emptyset$ 
18     for each vertex  $x \in A$ 
19     do  $status(x) = labeled$ 
20         for each edge  $(x, y) \in E$ 
21         do if  $d(x) + weight(x, y) < d(y)$ 
22             then  $d(y) \leftarrow d(x) + weight(x, y)$ 
23                 if  $status(y) = unreached$ 
24                     then  $B \leftarrow B \cup \{y\}$ 
25                      $status(y) \leftarrow labeled$ 
26                      $status(x) \leftarrow scanned$ 
27     until  $A$  is empty
28 return (SAT,  $\emptyset$ )
29
```

Some notes to the Algorithm 2:

- In practice, checking Γ_d for a cycle (line 9) and computing a set of vertices reachable from B (line 15) can be done by only one DFS call. However, it is two logically distinct steps and therefore they are performed separately in the algorithm.

- Unexplored vertices (line 15) are vertices which have status *unreached* i.e. they have not been processed yet at that particular step.
- If B is empty or no unexplored vertices are reachable from it (line 15) then A will be assigned an empty set.

The admissible graph Γ_d describes a set of possible path updates that can be used to improve distance estimates. If it contains a cycle then it means that one can update distance estimates infinitely by looping along this cycle. The idea of the Algorithm 2 is to det

Theorem 3.1 (Name of the theorem) *This is how you write a theorem. Do not forget to prove the theorem.*

Proof 3.1 *Here you write the proof of the theorem.*

3.5 Implementation Details

Some implementation details (Numeric Conflict Analysis, Reducing Feasibility Checks).

3.6 Experimental Results

Tell a reader about some experimental results.

4 Conclusion

Conclusion on the topic ($\frac{1}{2}$ of a page).

References

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