Verificare Formala Aplicatii ale SMT solving

Mădălina Erașcu

West University of Timișoara Faculty of Mathematics and Informatics Department of Computer Science

Bazat pe suportul de curs: Satisfiability Checking (Erika Ábrahám), RTWH Aachen
Bazat pe cartile: (1) The calculus of computation - Z. Manna, A. Bradley; (2) Decision Procedures - An algorithmic Point
of View - D. Kroening, O. Strichman

WS 2023/2024

Outline

1 Optimization

2 Example 1: Virtual Machine Placement

Contents

1 Optimization

2 Example 1: Virtual Machine Placement

General form:

Minimize/maximize $f_1(x, y, ...), f_2(x, y, ...), ..., f_n(x, y, ...)$ subject to C(x, y, ...).

General form:

Minimize/maximize $f_1(x, y, ...), f_2(x, y, ...), ..., f_n(x, y, ...)$ subject to C(x, y, ...).

■ Single optimization: $n \ge 1$

General form:

Minimize/maximize $f_1(x, y, ...), f_2(x, y, ...), ..., f_n(x, y, ...)$ subject to C(x, y, ...).

- Single optimization: $n \ge 1$
- Multiple optimization: $n \ge 2$

General form:

Minimize/maximize $f_1(x, y, ...), f_2(x, y, ...), ..., f_n(x, y, ...)$ subject to C(x, y, ...).

- Single optimization: $n \ge 1$
- Multiple optimization: $n \ge 2$

In the SMT solver Z3 (https://github.com/Z3Prover/z3), there are three ways to combine objective functions (assume we want to maximize):

General form:

Minimize/maximize $f_1(x, y, ...), f_2(x, y, ...), ..., f_n(x, y, ...)$ subject to C(x, y, ...).

- Single optimization: $n \ge 1$
- Multiple optimization: $n \ge 2$

In the SMT solver Z3 (https://github.com/Z3Prover/z3), there are three ways to combine objective functions (assume we want to maximize):

General form:

Minimize/maximize $f_1(x, y, ...), f_2(x, y, ...), ..., f_n(x, y, ...)$ subject to C(x, y, ...).

- Single optimization: $n \ge 1$
- Multiple optimization: $n \ge 2$

In the SMT solver Z3 (https://github.com/Z3Prover/z3), there are three ways to combine objective functions (assume we want to maximize):

General form:

Minimize/maximize $f_1(x, y, ...), f_2(x, y, ...), ..., f_n(x, y, ...)$ subject to C(x, y, ...).

- Single optimization: $n \ge 1$
- Multiple optimization: $n \ge 2$

In the SMT solver Z3 (https://github.com/Z3Prover/z3), there are three ways to combine objective functions (assume we want to maximize):

General form:

Minimize/maximize $f_1(x, y, ...), f_2(x, y, ...), ..., f_n(x, y, ...)$ subject to C(x, y, ...).

- Single optimization: $n \ge 1$
- Multiple optimization: $n \ge 2$

In the SMT solver Z3 (https://github.com/Z3Prover/z3), there are three ways to combine objective functions (assume we want to maximize):

where x, y are the decision variables, $\varphi(x, y)$ are the constraints to be fulfilled.

General form:

Minimize/maximize $f_1(x, y, ...), f_2(x, y, ...), ..., f_n(x, y, ...)$ subject to C(x, y, ...).

- Single optimization: $n \ge 1$
- Multiple optimization: $n \ge 2$

In the SMT solver Z3 (https://github.com/Z3Prover/z3), there are three ways to combine objective functions (assume we want to maximize):

- **1** $Box(x, y) : v_x := max\{x|\varphi(x, y)\}, v_y := max\{y|\varphi(x, y)\}$

where x, y are the decision variables, $\varphi(x, y)$ are the constraints to be fulfilled.

More details at

https://theory.stanford.edu/~nikolaj/programmingz3.html.

Optimization (cont'd)

In Z3, the default optimization is lexicographic.

One can set up other types of optimization by adding (SMT-LIB version, but there exists also the corresponding commands for Python API):

- (set-option :opt.priority pareto)
- (set-option :opt.priority box)

In multi-objective optimization, it is typically the the case that the objective functions are competing.

In multi-objective optimization, it is typically the the case that the objective functions are competing.

In this case, we talk about a set of optimal solutions instead of one optimal solution since no solution is better than the other.

In multi-objective optimization, it is typically the the case that the objective functions are competing.

In this case, we talk about a set of optimal solutions instead of one optimal solution since no solution is better than the other.

These optimal solutions are called Pareto-optimal solutions.

In multi-objective optimization, it is typically the the case that the objective functions are competing.

In this case, we talk about a set of optimal solutions instead of one optimal solution since no solution is better than the other.

These optimal solutions are called Pareto-optimal solutions.

Given a set of feasible solutions and different objective functions, Pareto improvement is a movement from one feasible solution to another that can make at least one objective function to return a better value with no other objective function becoming worse.

In multi-objective optimization, it is typically the the case that the objective functions are competing.

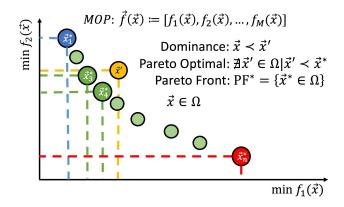
In this case, we talk about a set of optimal solutions instead of one optimal solution since no solution is better than the other.

These optimal solutions are called Pareto-optimal solutions.

Given a set of feasible solutions and different objective functions, Pareto improvement is a movement from one feasible solution to another that can make at least one objective function to return a better value with no other objective function becoming worse.

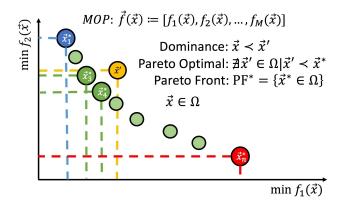
A set of feasible solutions are Pareto efficient/optimal when no further Pareto improvements can be made.

Solutions along the line are all non-dominated solutions.



Solutions along the line are all non-dominated solutions.

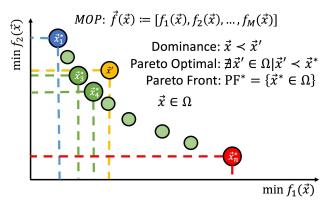
Dominated solutions are inside the line as there is another solution on the line with at least one objective that is better.



Solutions along the line are all non-dominated solutions.

Dominated solutions are inside the line as there is another solution on the line with at least one objective that is better.

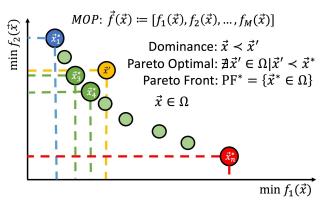
The line is the Pareto-optimal front and the solutions on it are called Pareto-optimal.



Solutions along the line are all non-dominated solutions.

Dominated solutions are inside the line as there is another solution on the line with at least one objective that is better.

The line is the Pareto-optimal front and the solutions on it are called Pareto-optimal. All Pareto optimal solutions are non-dominated.



Contents

1 Optimization

2 Example 1: Virtual Machine Placement

Virtual Machine Placement Problem

Assume that we have three virtual machines (VMs) which require 100, 50 and 15 GB hard disk respectively. There are three servers with capabilities 100, 75 and 200 GB in that order. Find out a way to place VMs into servers in order to:

- Minimize the operation cost (the servers have fixed daily costs 10, 5 and 20 USD respectively.)
- 2 Minimize the number of servers used.

Virtual Machine Placement Problem

Assume that we have three virtual machines (VMs) which require 100, 50 and 15 GB hard disk respectively. There are three servers with capabilities 100, 75 and 200 GB in that order. Find out a way to place VMs into servers in order to:

- Minimize the operation cost (the servers have fixed daily costs 10, 5 and 20 USD respectively.)
- 2 Minimize the number of servers used.

Solution. We first formalize the problem. Then we can translate it into the SMT-LIB format and use an SMT solver to find a solution.

Virtual Machine Placement Problem

Assume that we have three virtual machines (VMs) which require 100, 50 and 15 GB hard disk respectively. There are three servers with capabilities 100, 75 and 200 GB in that order. Find out a way to place VMs into servers in order to:

- Minimize the operation cost (the servers have fixed daily costs 10, 5 and 20 USD respectively.)
- 2 Minimize the number of servers used.

Solution. We first formalize the problem. Then we can translate it into the SMT-LIB format and use an SMT solver to find a solution.

Let x_{ij} denote that VM i is placed on the server j and y_j denote that server j is in use.

We need to express the followings.

Implicit constraints

Explicit constraints

- Implicit constraints
 - A VM is on exactly one server:

$$x_{i1} + x_{i2} + x_{i3} = 1, \quad \forall i, j = \overline{1,3}$$

Explicit constraints

- 1 Implicit constraints
 - A VM is on exactly one server:

$$x_{i1} + x_{i2} + x_{i3} = 1, \quad \forall i, j = \overline{1,3}$$

A used server has at least a VM on it:

$$(x_{1j} = 1) \lor ... \lor (x_{3j} = 1) \Rightarrow (y_j = 1), j = \overline{1,3}$$

Explicit constraints

- Implicit constraints
 - A VM is on exactly one server:

$$x_{i1} + x_{i2} + x_{i3} = 1$$
, $\forall i, j = \overline{1,3}$

A used server has at least a VM on it:

$$(x_{1j} = 1) \lor ... \lor (x_{3j} = 1) \Rightarrow (y_j = 1), j = \overline{1,3}$$

- Explicit constraints
 - Capacity constraints:

$$100x_{11} + 50x_{21} + 15x_{31} \le 100y_1$$

$$100x_{12} + 50x_{22} + 15x_{32} \le 75y_2$$

$$100x_{13} + 50x_{23} + 15x_{33} \le 200y_3$$

- Implicit constraints
 - A VM is on exactly one server:

$$x_{i1} + x_{i2} + x_{i3} = 1$$
, $\forall i, j = \overline{1,3}$

A used server has at least a VM on it:

$$(x_{1j} = 1) \lor ... \lor (x_{3j} = 1) \Rightarrow (y_j = 1), j = \overline{1,3}$$

- Explicit constraints
 - Capacity constraints:

$$100x_{11} + 50x_{21} + 15x_{31} \le 100y_1$$

$$100x_{12} + 50x_{22} + 15x_{32} \le 75y_2$$

$$100x_{13} + 50x_{23} + 15x_{33} \le 200y_3$$

- Optimization functions
 - $10y_1 + 5y_2 + 20y_3$

- Implicit constraints
 - A VM is on exactly one server:

$$x_{i1} + x_{i2} + x_{i3} = 1, \quad \forall i, j = \overline{1,3}$$

A used server has at least a VM on it:

$$(x_{1j} = 1) \lor ... \lor (x_{3j} = 1) \Rightarrow (y_j = 1), j = \overline{1,3}$$

- Explicit constraints
 - Capacity constraints:

$$100x_{11} + 50x_{21} + 15x_{31} \le 100y_1$$

$$100x_{12} + 50x_{22} + 15x_{32} \le 75y_2$$

$$100x_{13} + 50x_{23} + 15x_{33} \le 200y_3$$

- 3 Optimization functions
 - $10y_1 + 5y_2 + 20y_3$
 - $v_1 + y_2 + y_3$

There are various ways of encoding the variables of the problem, for example:

```
(Variant 1) as integers
(Variant 2) as real
(Variant 3) as bool
(Variant 4) using assert-soft constraints
```

There are various ways of encoding the variables of the problem, for example:

```
(Variant 1) as integers
(Variant 2) as real
(Variant 3) as bool
(Variant 4) using assert-soft constraints
```

Variant 1.

There are various ways of encoding the variables of the problem, for example:

```
(Variant 1) as integers
(Variant 2) as real
(Variant 3) as bool
```

(Variant 4) using assert-soft constraints

Variant 1. We declare each variable as integer, e.g.:

We also need to ensure that variables are 0/1, e.g.:

Another variant for encoding the 0/1 integers is:

```
(assert (or (>= x11 0) (<= x11 1)
(assert (or (>= x12 0) (<= x12 1)...
```

There are various ways of encoding the variables of the problem, for example:

```
(Variant 1) as integers
(Variant 2) as real
(Variant 3) as bool
(Variant 4) using assert-soft constraints
Variant 1. Constraint of type 2 can be encoded in 2 ways. For example:
    (assert (and (>= y1 x11) (>= y1 x21) (>= y1 x31)))
...
```

Or as:

...

```
(assert (implies (= y1 1) (or (= x11 1) (= x21 1) (= x31 1) ))
```

There are various ways of encoding the variables of the problem, for example:

```
(Variant 1) as integers
(Variant 2) as real
(Variant 3) as bool
(Variant 4) using assert-soft constraints
```

Variant 2. We declare each variable as real. The constraints should be the same as for the integer encoding.

There are various ways of encoding the variables of the problem, for example:

```
(Variant 1) as integers
(Variant 2) as real
(Variant 3) as bool
(Variant 4) using assert-soft constraints
```

Variant 3. We declare each variable as bool. The capability constraints require only integer/real variables, so we need to transform the bool variables into integer/real. This can be done by declaring a function as follows:

```
(define-fun bool_to_int ((b Bool)) Int (ite b 1 0) )
and cast the bool variables to int/real, e.g.
(assert (<= (+ (* 100 (bool_to_int x11)) ... ) (...)))</pre>
```

There are various ways of encoding the variables of the problem, for example:

```
(Variant 1) as integers
(Variant 2) as real
(Variant 3) as bool
(Variant 4) using assert-soft constraints
```

Variant 4. Use assert-soft constraints (soft constraints) (see https://rise4fun.com/Z3/tutorialcontent/optimization). For our problem, soft constraints can be used to encode the optimization goals: (assert-soft (not y1) :id num_servers) ... (assert-soft (not y1) :id costs :weight 10) ... The assert-soft command represents MaxSMT (maximize the number of constraints which can be satisfied) which tries to maximize the weighted sum of boolean expressions belonged to the same id. Since we are doing minimization, negation is needed to take advantage of MaxSMT support.