Incremental Maximum Satisfiability

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Maximum satisfiability (MaxSAT)

Bacchus, Järvisalo, and Martins [2021]

- Optimization paradigm based on Boolean satisfiability (SAT)
  - *minimize:* linear objective function over 0-1 variables
  - *subject to:* constraints expressed in propositional logic
- Suitable **declarative modelling language** for various real-world optimization problems involving **logical constraints**
  - verification of hardware and software
  - planning and scheduling
  - interpretable machine learning
  - ...
- Significant **progress in solving technology** over the past 20 years
  - multiple different native solving algorithms
  - state-of-the-art solvers build on the success of SAT solvers

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Incremental optimization *(a.k.a. reoptimization)*

- Various problem domains call for iterative solving procedures where **a sequence of related instances are solved**
  - types of incremental changes applied between instances:
    - adding or removing constraints
    - modifying objective function
- Solving each instance from scratch often too costly: **reuse information obtained during previous calls**
- Incremental SAT solving well-established Eén and Sörensson [2003]
  - extensively applied by MaxSAT solvers
- Application scenarios for incremental MaxSAT known, but...
- Currently **MaxSAT solvers offer limited support** for incrementality

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Contributions

Niskanen, Berg, and Järvisalo [2021, 2022]

1. Detail **various forms of incrementality in MaxSAT**
   - adding constraints, changing objective, assumptions
2. Propose **IPAMIR: incremental API for MaxSAT**
   - generic interface for developing incremental MaxSAT solvers and applications making use of incremental MaxSAT
   - MaxSAT Evaluation 2022: incremental track
3. Develop a fully-fledged **incremental MaxSAT solver**
   - support for all functionality specified in IPAMIR
   - extends MaxHS: the state-of-the-art implicit hitting set based solver
4. Provide **empirical evidence on benefits of incrementality**

Implementation and benchmark data openly available:
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  - linear objective function
- Goal: find an assignment which satisfies all hard constraints and minimizes the objective function

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Optimal solution:
$x = 1,\ y = 0,\ z = 0$

Incremental MaxSAT

- Aim for solving a sequence of related MaxSAT instances efficiently, avoiding computation from scratch
- Different scenarios call for different forms of incremental changes
  - adding or removing hard constraints
  - modifying the objective function
  - solving under assumptions: partial assignments to variables

Adding hard constraints

Example

Consider an initial problem instance, and an iterative procedure:

- Compute an optimal solution to the current instance
- Check whether it satisfies a desired property:
  if not, exclude it (and other non-solutions) from consideration

Generic paradigm with various instantiations employing MaxSAT

Mangal, Zhang, Nori, and Naik [2015]; Niskanen and Järvisalo [2020]

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Changing coefficients

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Learning classifiers with the AdaBoost algorithm: MaxSAT employed for decision trees Hu, Siala, Hebrard, and Huguet [2020]

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Optimizing under assumptions

Example

Consider an initial problem instance, and an iterative procedure:

- Extract information about the current state of the world
- Incorporate it to the instance and compute an optimal solution

Timetabling under disruptions: time or room slots may become unavailable

Lemos, Monteiro, and Lynce [2020]

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  - for MaxSAT solvers providing support for incrementality
  - for applications making use of incrementality
- Builds on IPASIR: standard interfaca for incremental SAT
- Specifies incremental changes to a MaxSAT instance
  - adding hard constraints
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  - assumptions on variables
- Includes other essential declarations
  - constructing and releasing a solver
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IPAMIR: Incremental API for MaxSAT

```
// Construct a MaxSAT solver and return a pointer to it.
void * ipamir_init ();
// Deallocate all resources of the MaxSAT solver.
void ipamir_release (void * solver);
// Add a literal to a hard clause or finalize the clause with zero.
void ipamir_add_hard (void * solver, int32_t lit_or_zero);
// Add a weighted soft literal.
void ipamir_add_soft_lit (void * solver, int32_t lit, uint64_t weight);
// Assume a literal for the next solver call.
void ipamir_assume (void * solver, int32_t lit);
// Solve the MaxSAT instance under the current assumptions.
int ipamir_solve (void * solver);
// Compute the cost of the solution.
uint64_t ipamir_val_obj (void * solver);
// Extract the truth value of a literal in the solution.
int32_t ipamir_val_lit (void * solver, int32_t lit);
// Set a callback function for terminating the solving procedure.
void ipamir_set_terminate (void * solver, void * state,
                           int (*terminate)(void * state));
```

Interface and example applications openly available:
https://bitbucket.org/coreo-group/ipamir

Implicit Hitting Set (IHS) based MaxSAT solving

Davies and Bacchus [2011, 2013]

An iterative approach: identify *sources of inconsistency* and *repair the inconsistencies* in a minimal way.

- Central notion: a *core* is an assignment to a subset of the objective function which cannot be extended to satisfy the hard constraints
  - SAT solver as *core extractor*
- *hs* is a *hitting set* over a set of cores $\mathcal{C}$ if *hs* intersects each $\kappa \in \mathcal{C}$
  - *cost* of a hitting set determined by coefficients of the objective
  - IP solver for computing *minimum-cost* hitting sets

Reasoning and *optimization* effectively decoupled:

- *upper bounds* from assignments given by the SAT solver
- *lower bounds* from costs of optimal hitting sets

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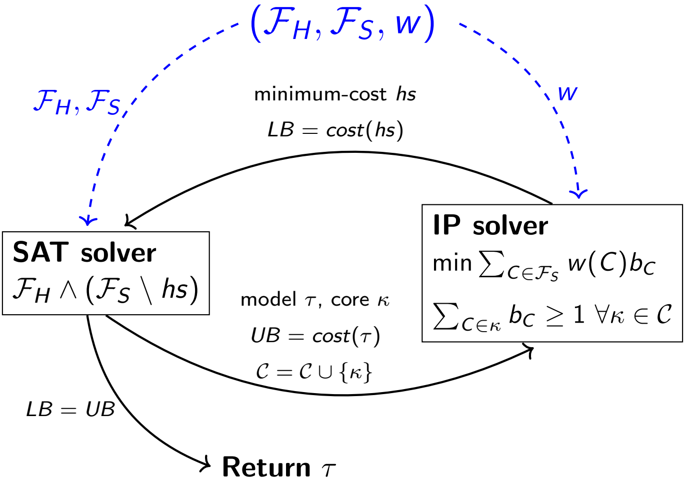

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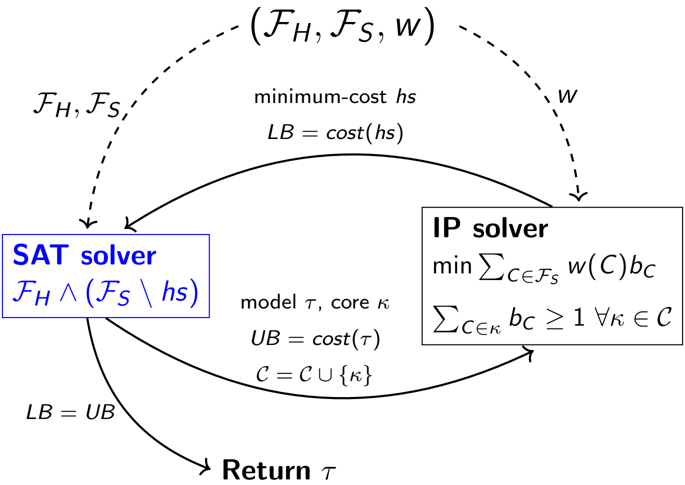

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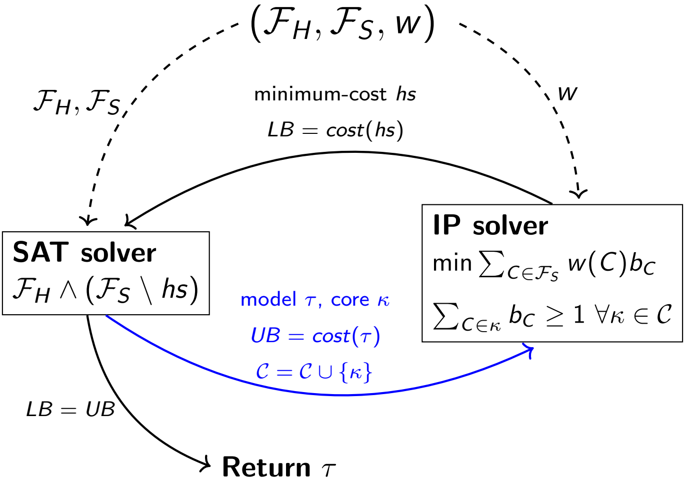

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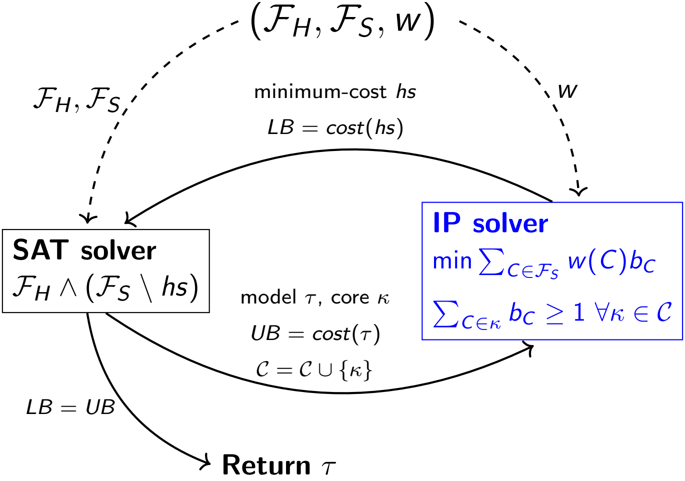

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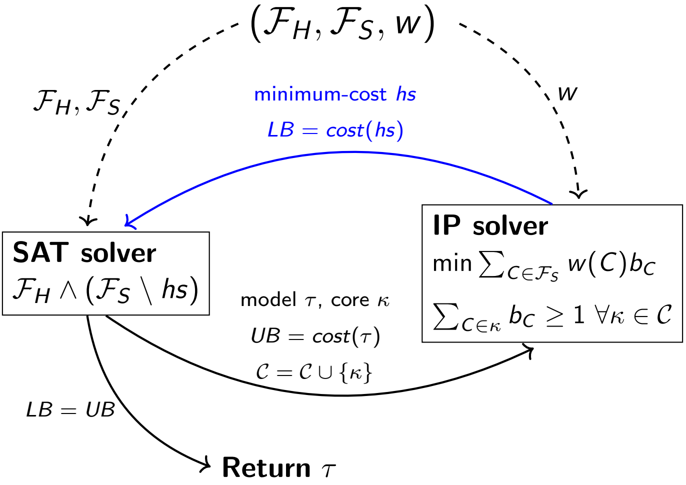

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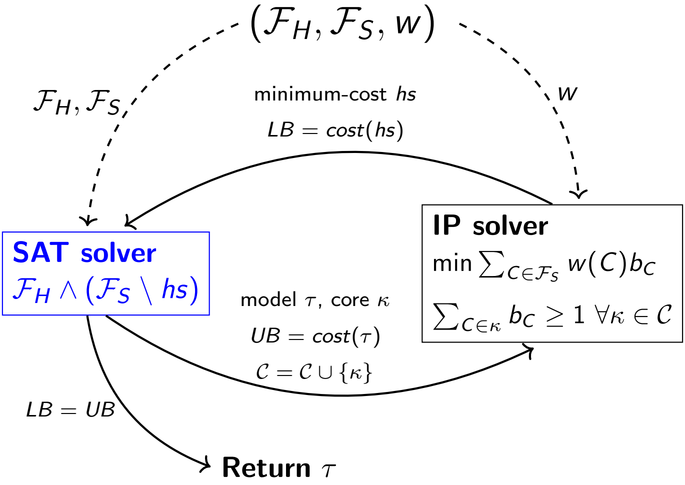

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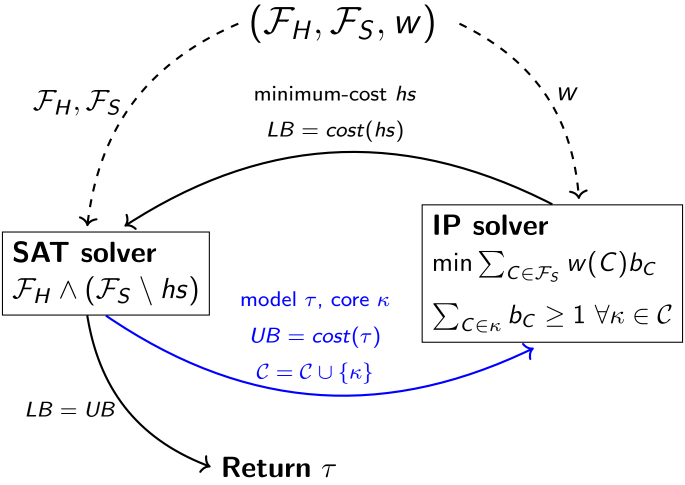

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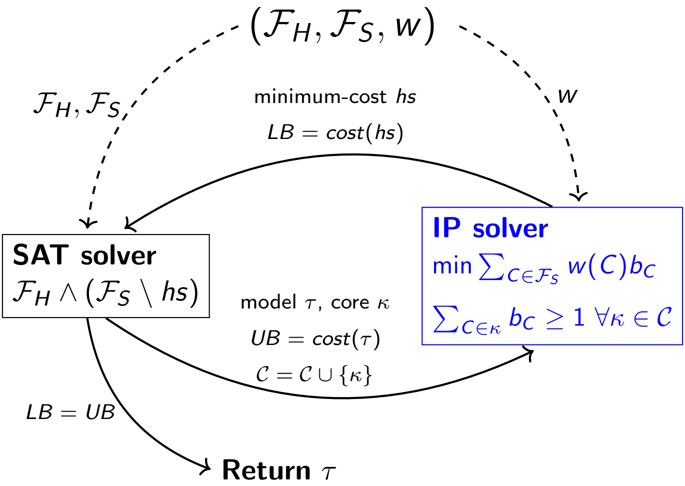

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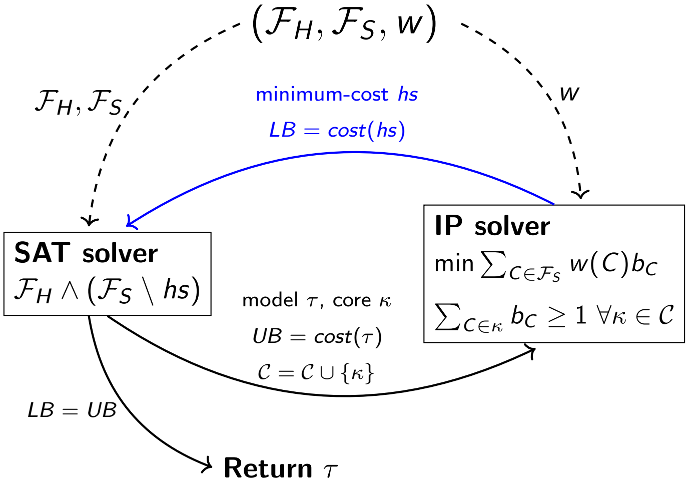

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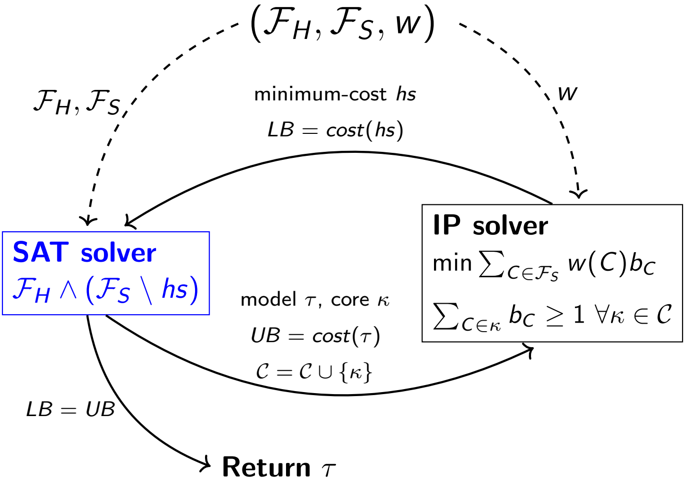

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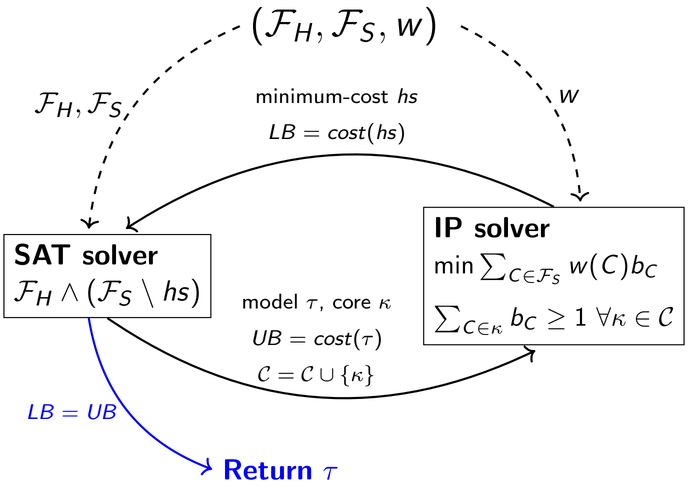

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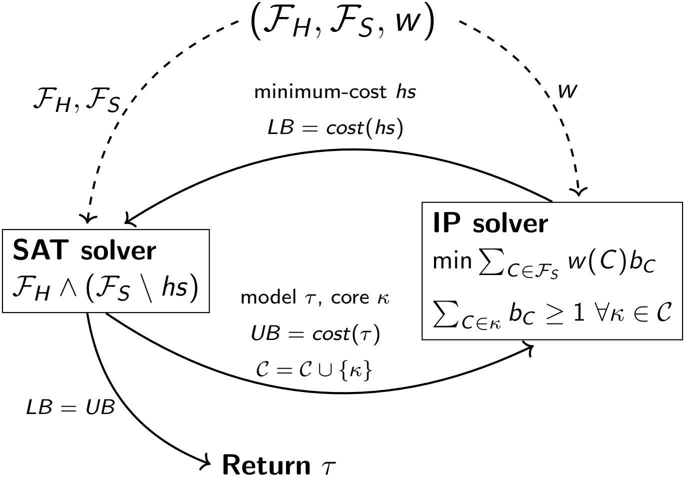

Incremental IHS

In theory

Observations:

- If we add a new hard clause, a term to the objective function, or change coefficients, **all extracted cores are still valid**
    - **cores can be preserved** between solver invocations
    - only objective needs to be altered in the IP solver
- The SAT solver knows nothing about the objective
    - add hard clauses directly to the SAT solver
    - no need to reinitialize

Assumptions require more care: the notion of *conditional cores* take into account the assumptions made during core extraction

- still, **no need to reset the SAT solver**
- however, IP solver reinitialized with *restrictions* of all conditional cores that are valid under current assumptions

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In practice

Make use of **MaxHS: state-of-the-art IHS-based MaxSAT solver**.
Realizing incrementality requires a non-trivial amount of engineering.

- **Simplification:** when initialized, MaxHS performs several rounds of simplification to the input MaxSAT instance
  - variable mappings between internal and external representations
  - fixed variables need to be handled correctly
  - ...
- **Maintaining conditional cores:** use another SAT solver as a database for storing conditional cores
  - removes redundant cores and simplifies them
- **Other techniques:** must be modified to preserve correctness
  - reduced cost fixing — Bacchus, Hyttinen, Järvisalo, and Saikko [2017]
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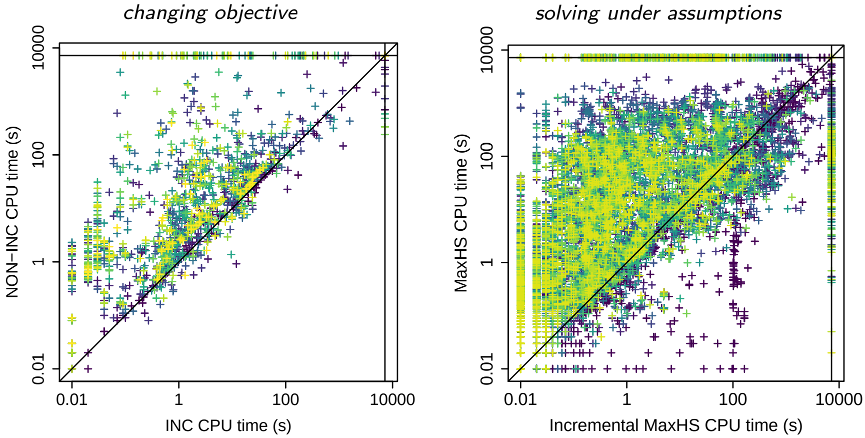
Empirical evaluation

Increased performance gained by preserving cores:



- blue points → earlier iterations
- yellow points → later iterations

Summary

Contributions

- **IPAMIR:** incremental API for MaxSAT
  - details various forms of incrementality in MaxSAT
  - provides a standard interface to facilitate the development of solvers and applications
- **Incremental MaxHS:** fully-fledged incremental MaxSAT solver
  - supports all IPAMIR functionality
  - preserves cores and does not reset SAT solver between invocations
- **Empirical evaluation:** clear benefit from incrementality

Implementation available online in open source:
`https://bitbucket.org/coreo-group/incremental-maxhs`

Thank you for your attention!

Get in touch via email:
`andreas.niskanen@helsinki.fi`

Or come chat in person :)

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