Enabling Incrementality in the Implicit Hitting Set Approach to MaxSAT under Changing Weights

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Online

Motivation

- MaxSAT: declarative optimisation based on propositional logic.
  - i.e. Boolean literals and clauses
- State-of-the-art solvers build on the success of CDCL SAT solvers.
- New application domains and solver improvements annually.

(Recent survey in [Bacchus, Järvisalo, and Martins, 2021])

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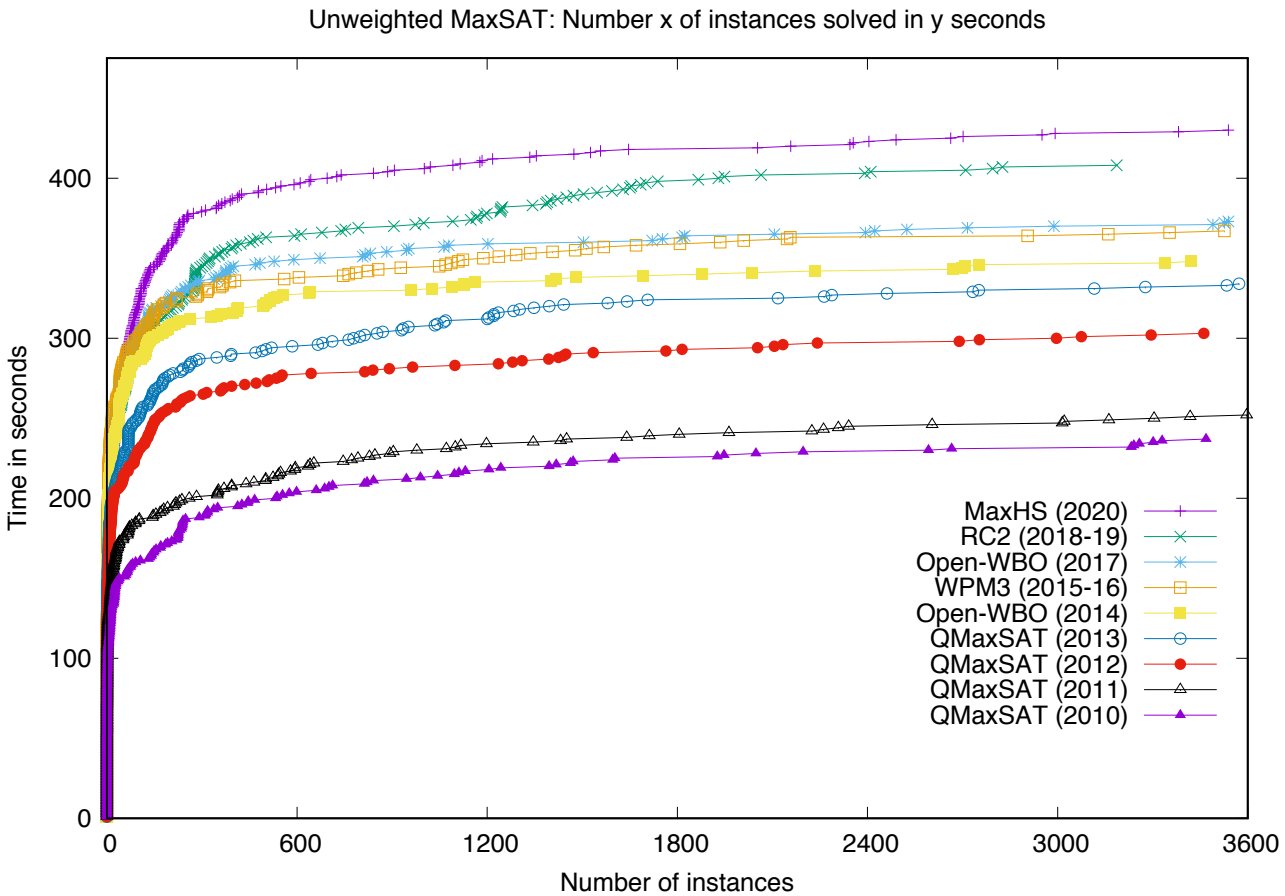

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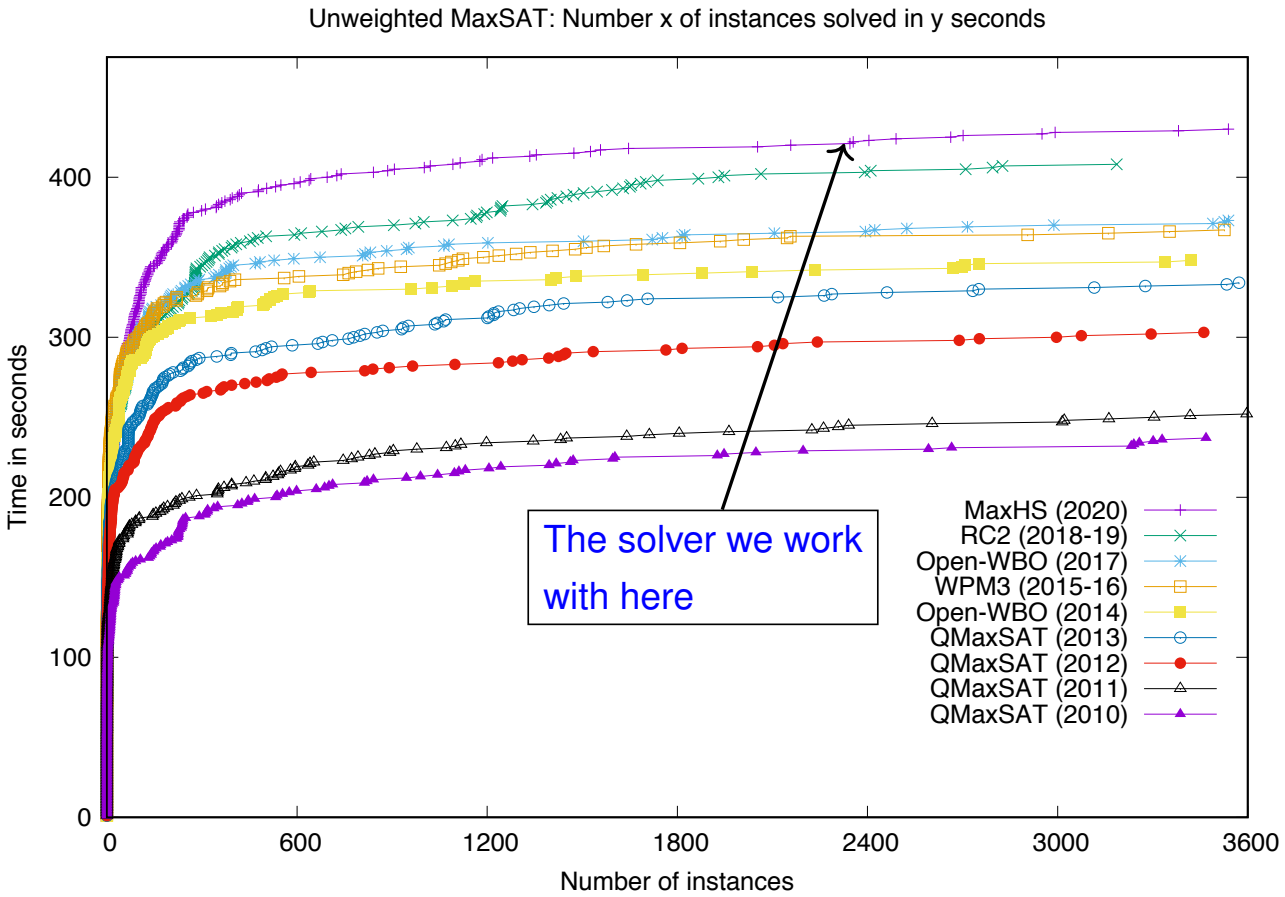

Incremental Optimisation

- *Incremental solving* $\rightarrow$ solving a sequence of similar instances.
- Incremental SAT solving:
  - well established
  - extensively applied (e.g. by MaxSAT solvers).
- Applications for incremental MaxSAT known
  - XAI
  - predict & optimize
  - markov logic networks
  - ...
- So far, very little support from solvers
  - adding clauses.
  - restarting core-guided search when search stagnates.

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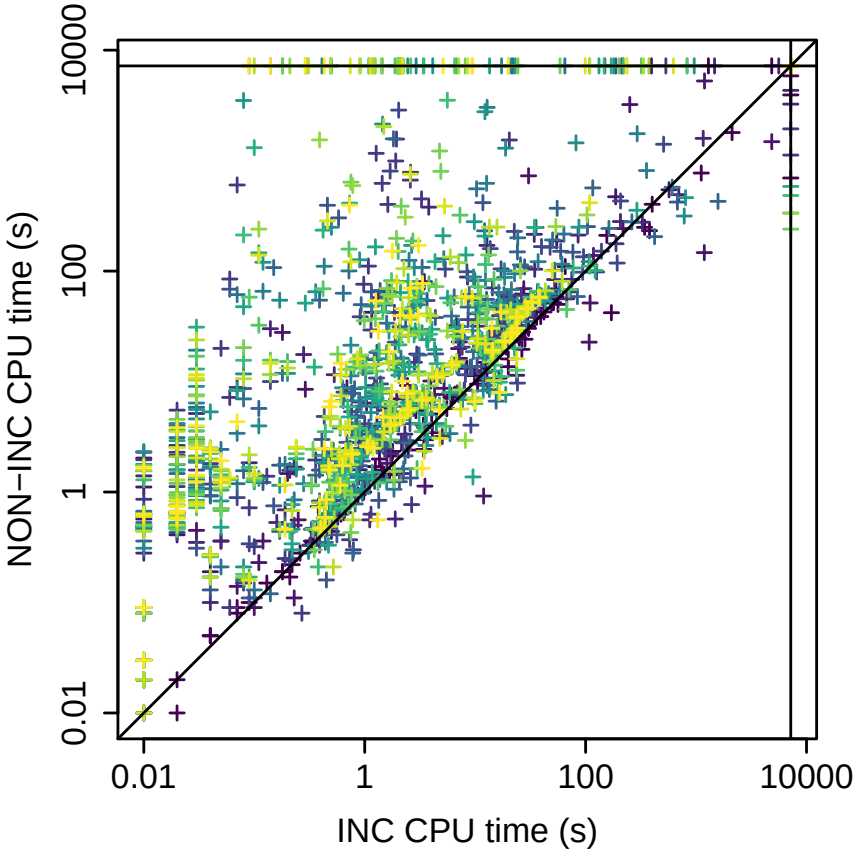
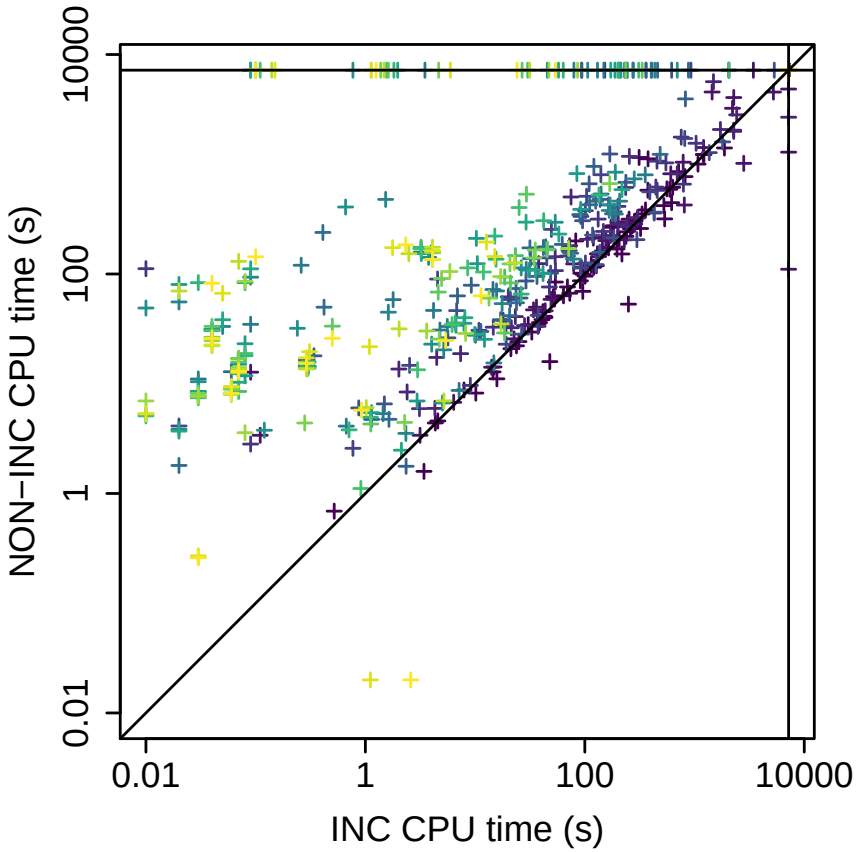
Our Contributions

An extension of the IHS solver MaxHS that supports changing weights incrementally



decision rules (MLIC)
[Malioutov and Meel, 2018]



decision trees (AdaBoost)
[Hu, Siala, Hebrard, and Huguet, 2020]

- blue points $\rightarrow$ earlier iterations
- yellow points $\rightarrow$ later iterations

Outline

- Preliminaries
- The Implicit Hitting Set (IHS) based approach to MaxSAT
- Incremental IHS
- Case Studies
- Conclusions

Preliminaries: Maximum Satisfiability

- Optimisation extension of Boolean Satisfiability (SAT)
- An instance consists of:
  - a set of hard clauses,
  - a set of soft clauses and
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- Central in modern MaxSAT solving (including IHS).
- $\kappa \subset \mathcal{F}_S$ is an *core* if $\mathcal{F}_H \wedge \kappa$ is unsatisfiable

Cores in IHS MaxSAT

$$\sum_{C \in hs} w(C) \leq cost(\mathcal{F})$$

for a minimum-cost hitting set *hs* over *any* set of core.

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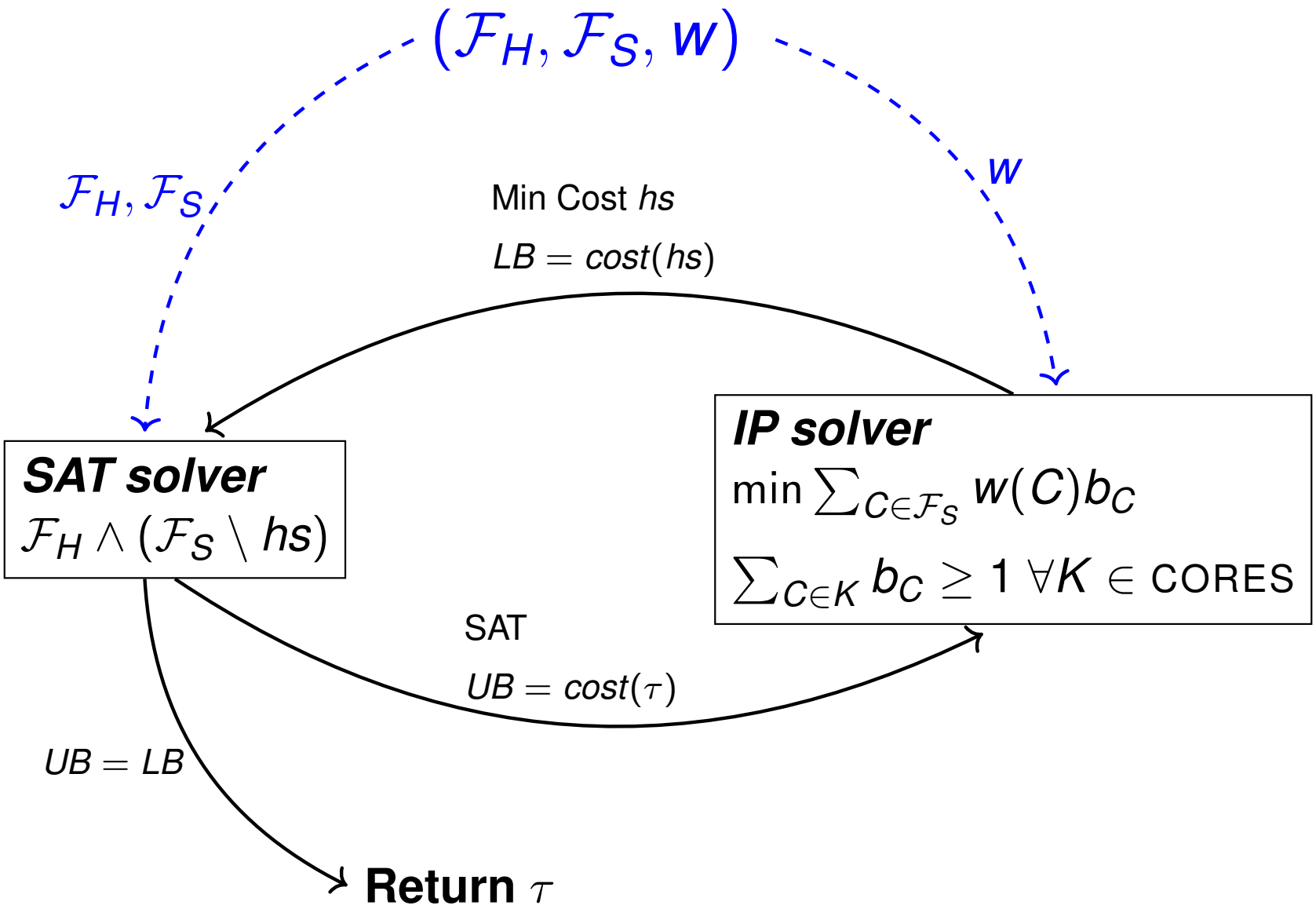
The IHS approach to MaxSAT

[Davies and Bacchus, 2011]



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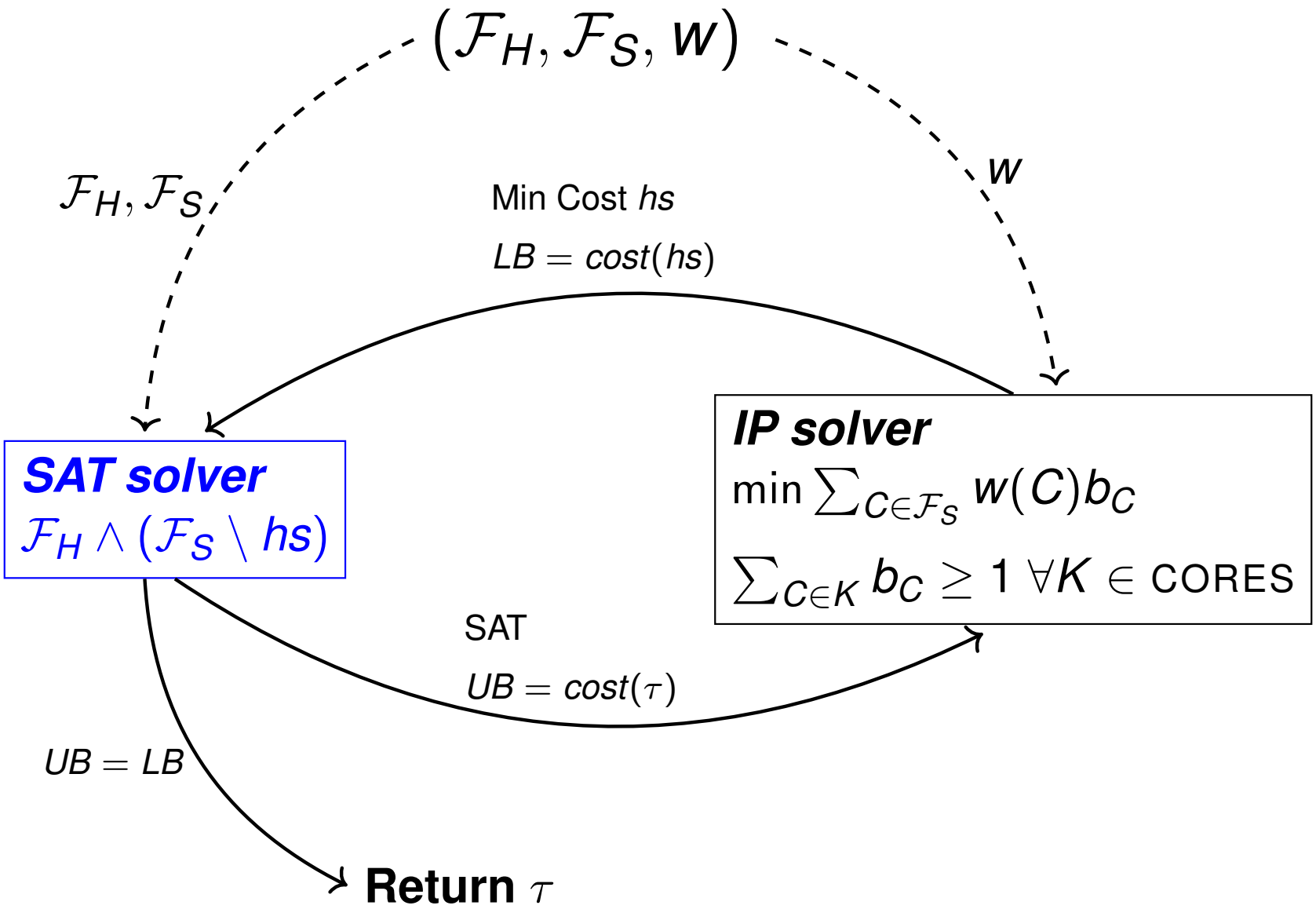

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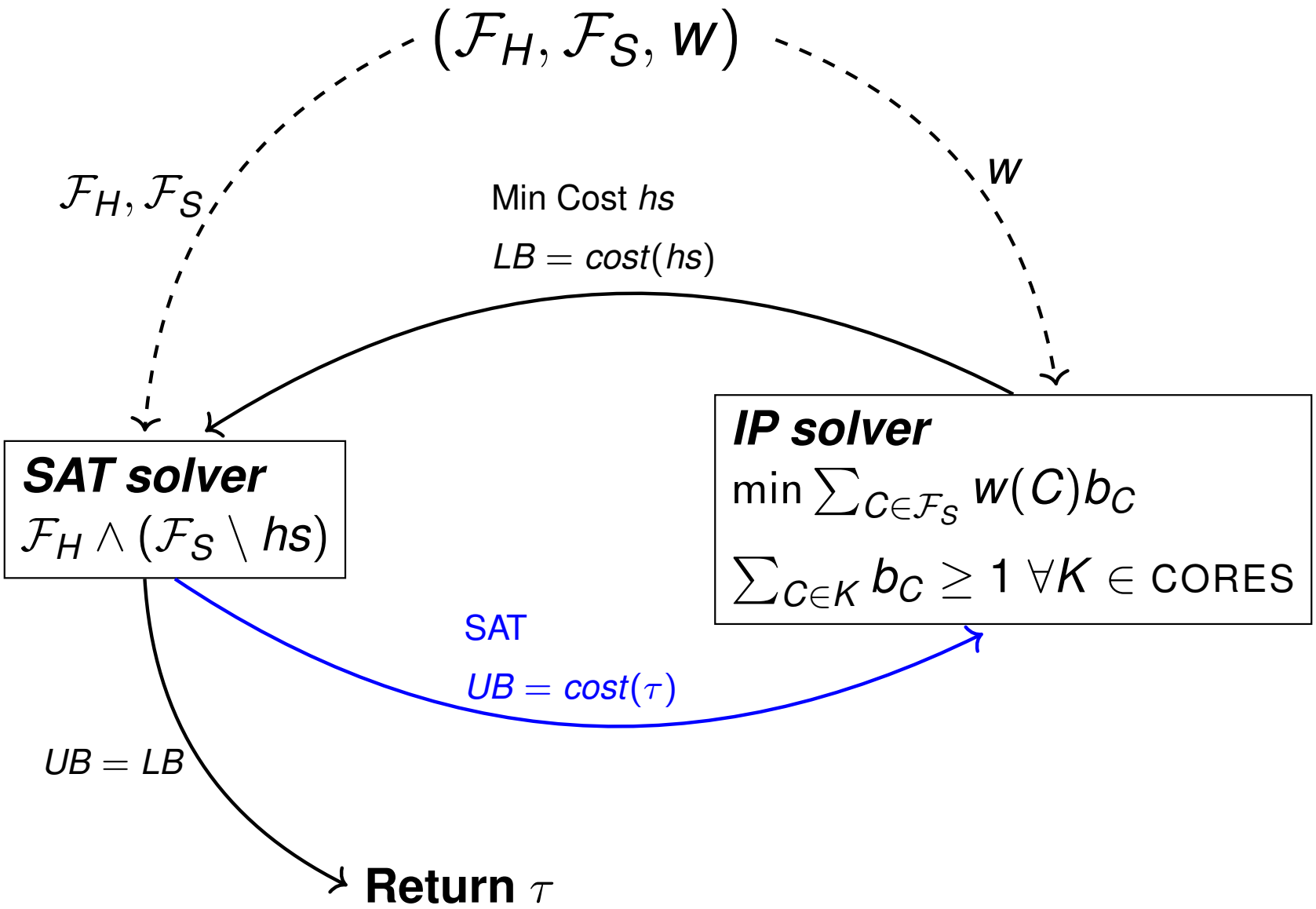

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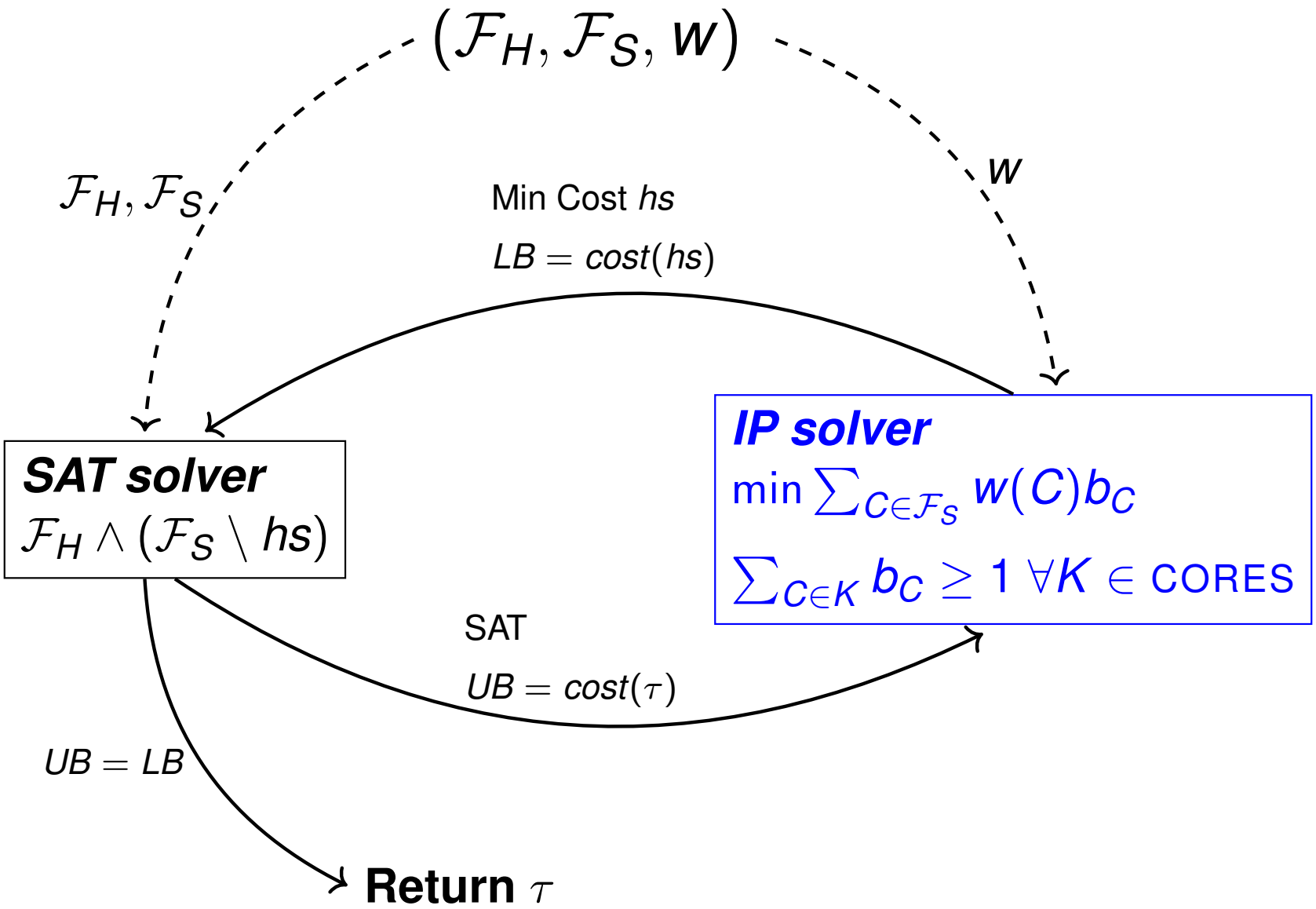

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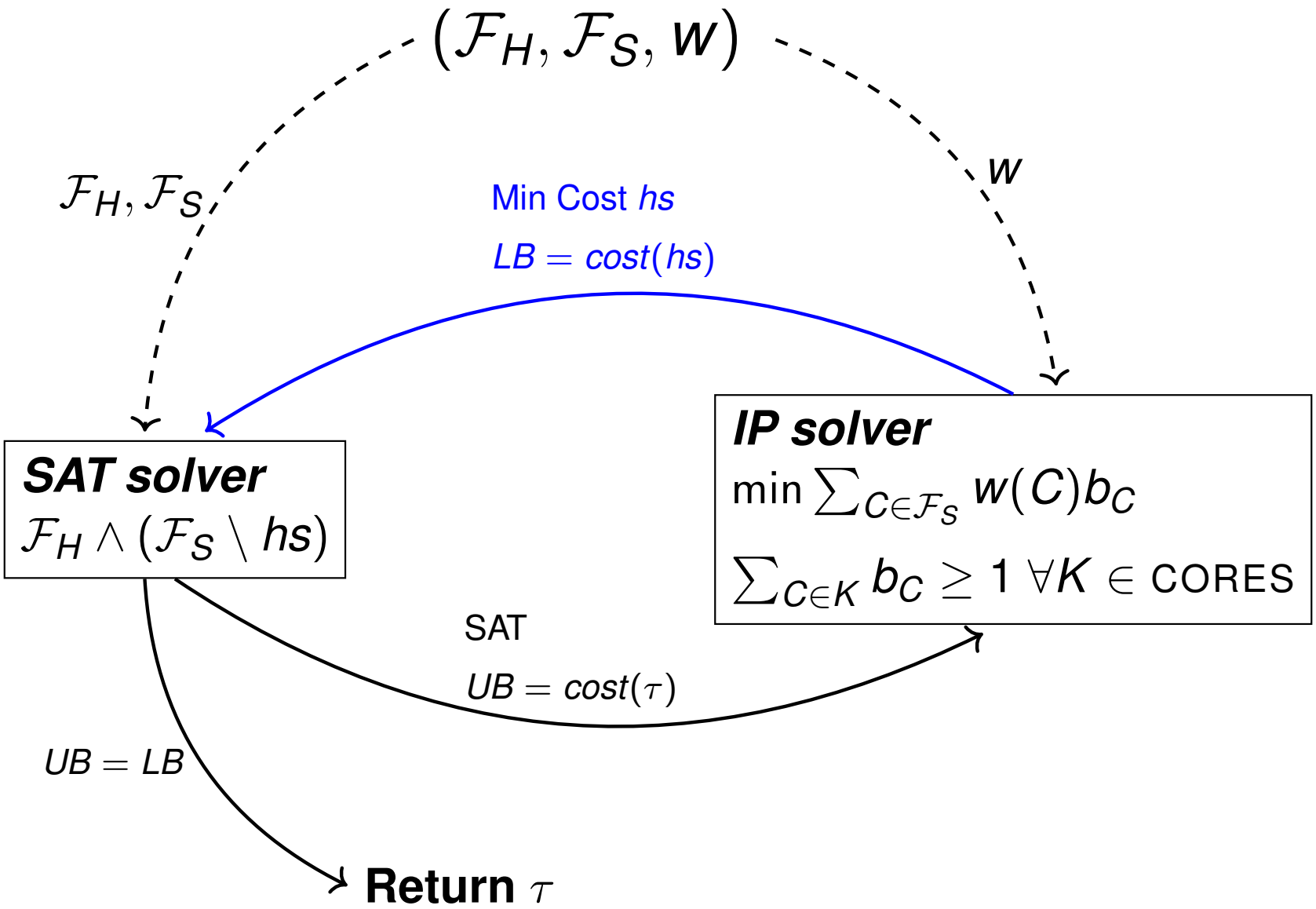

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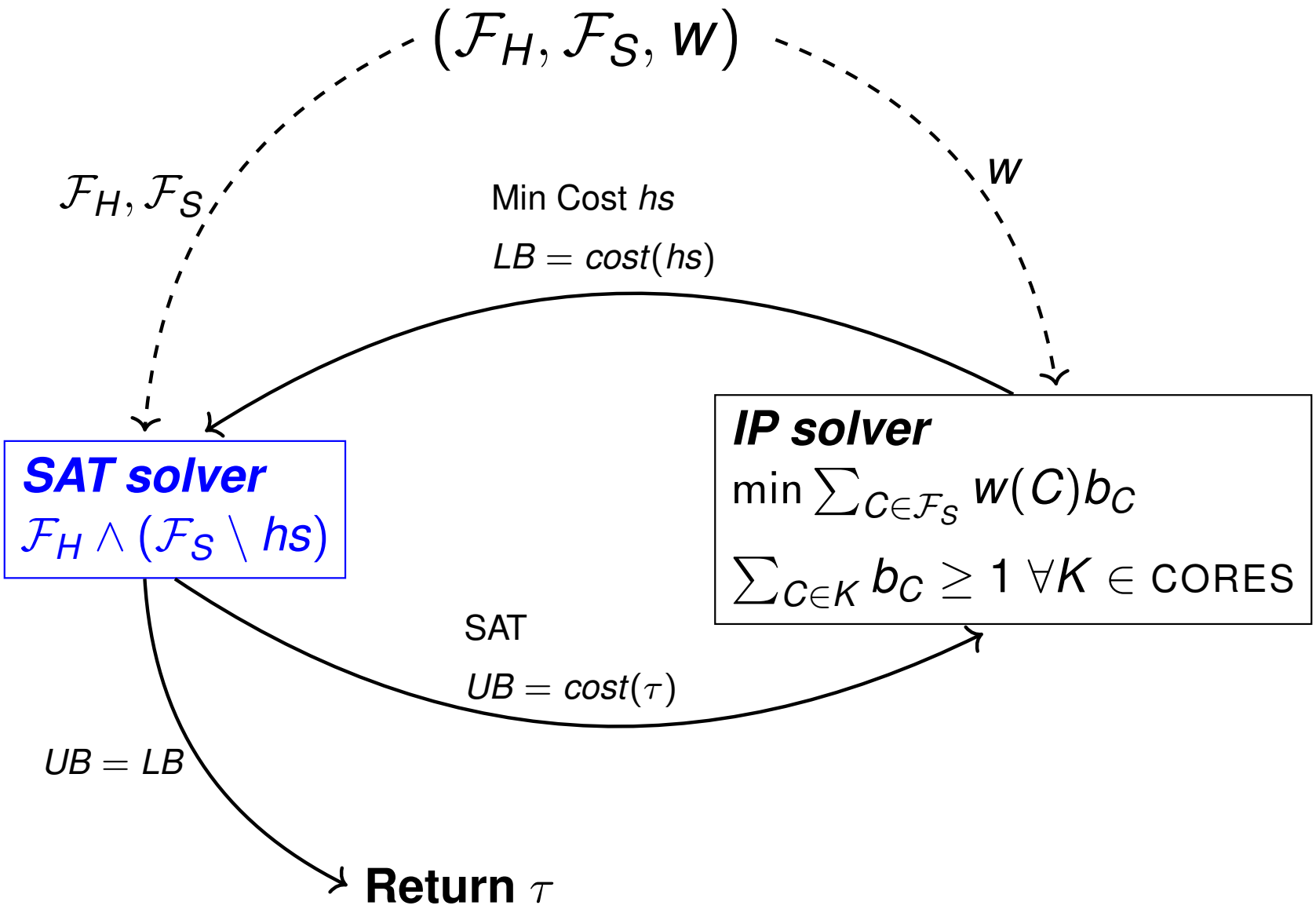

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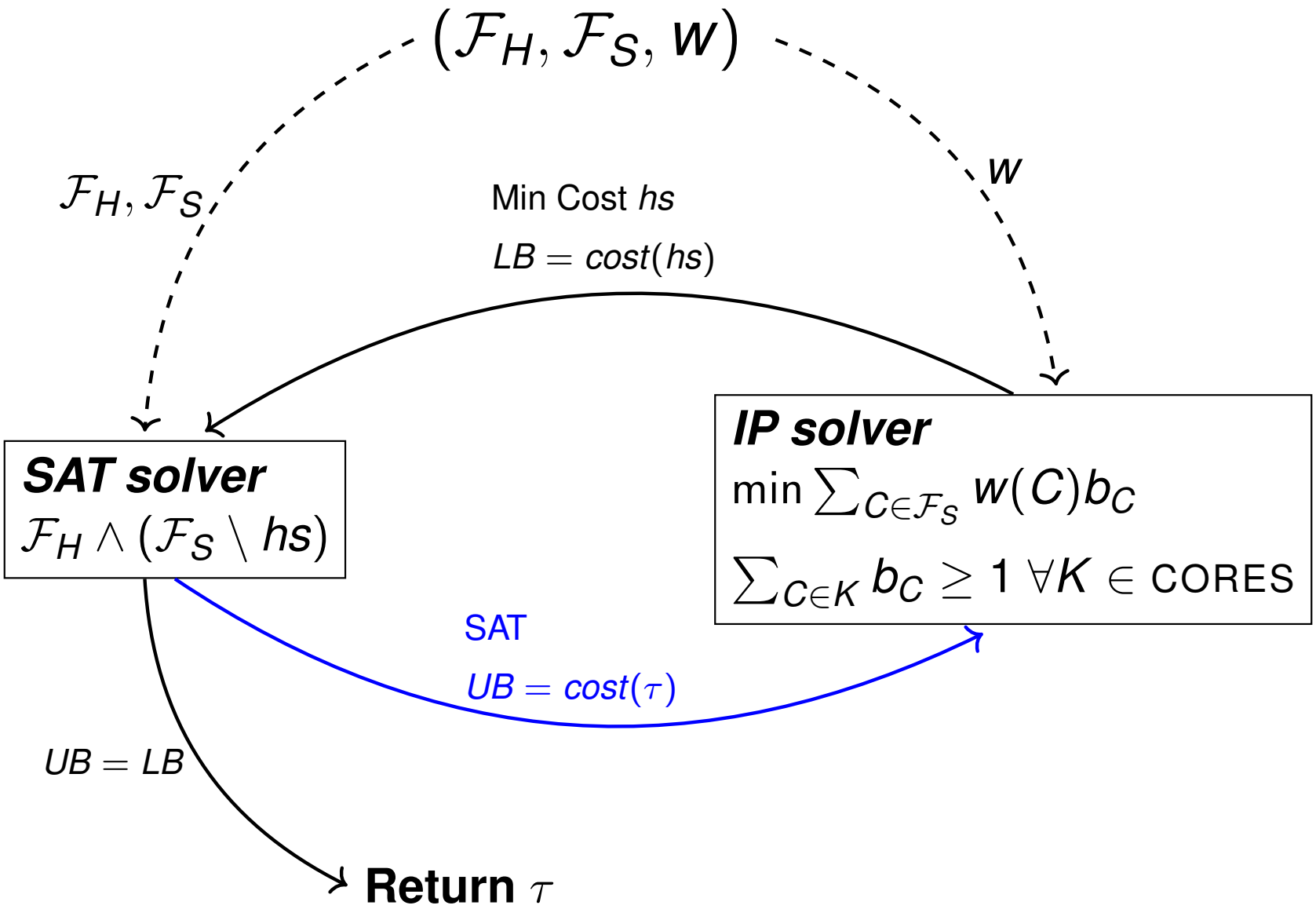

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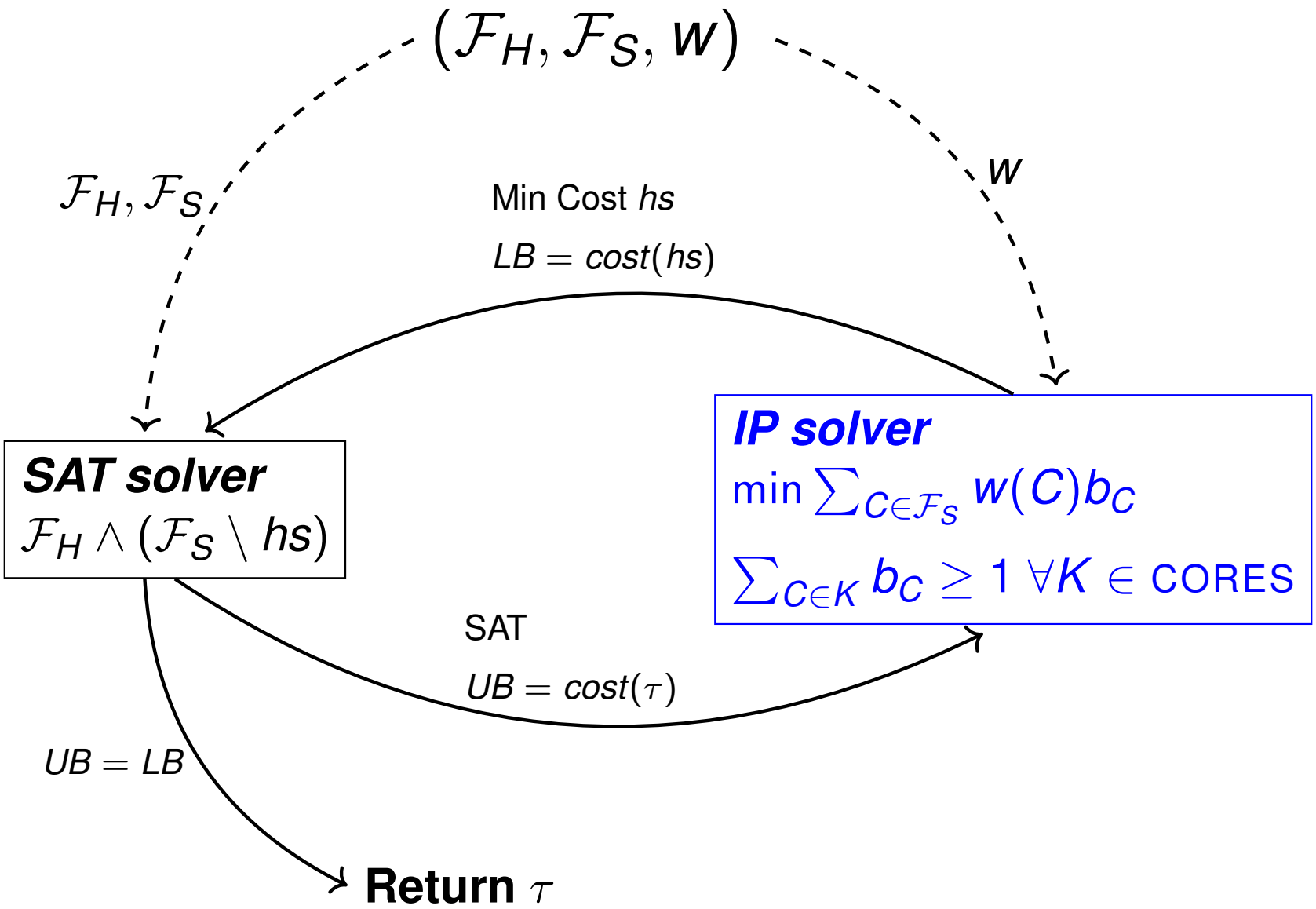

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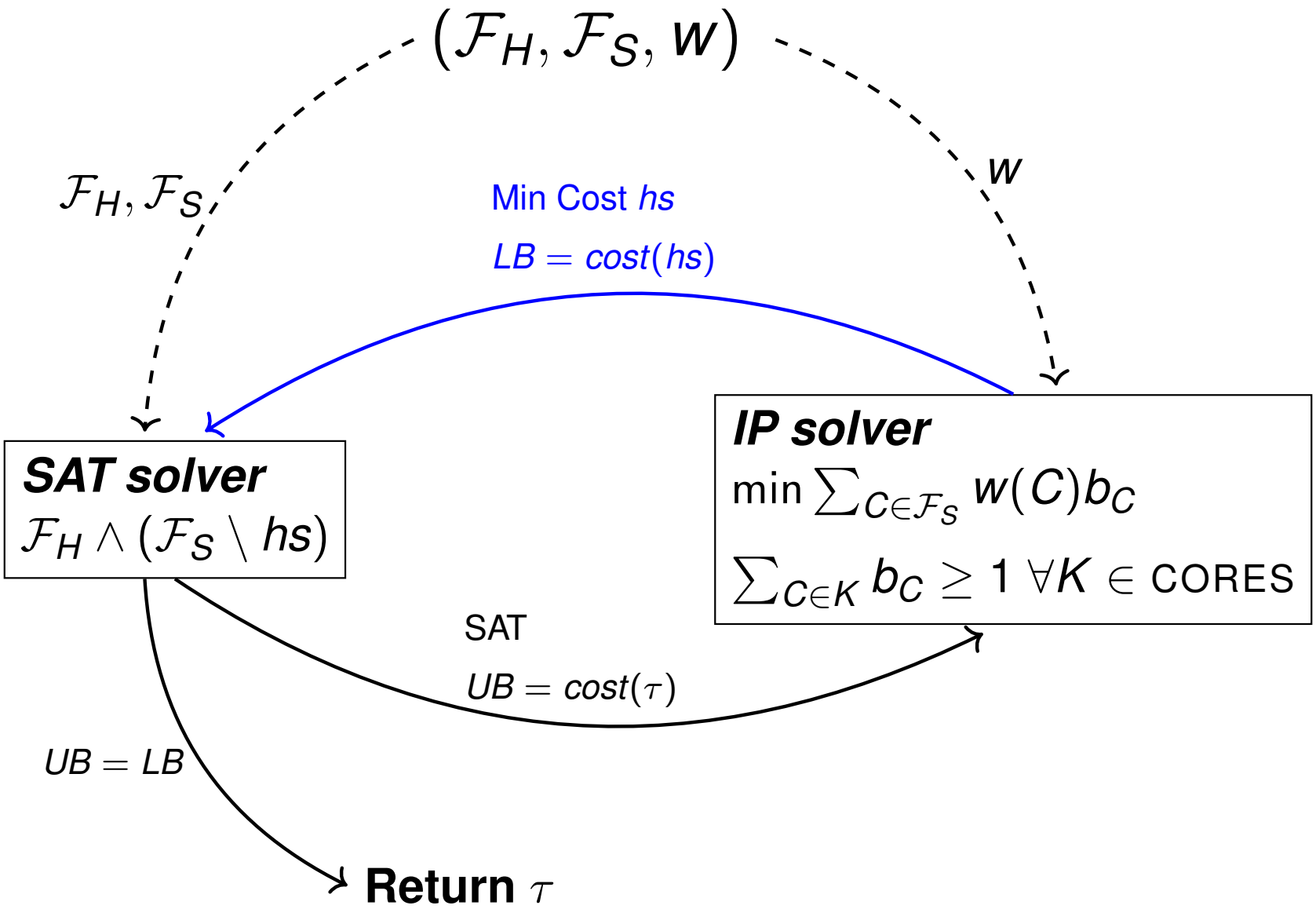

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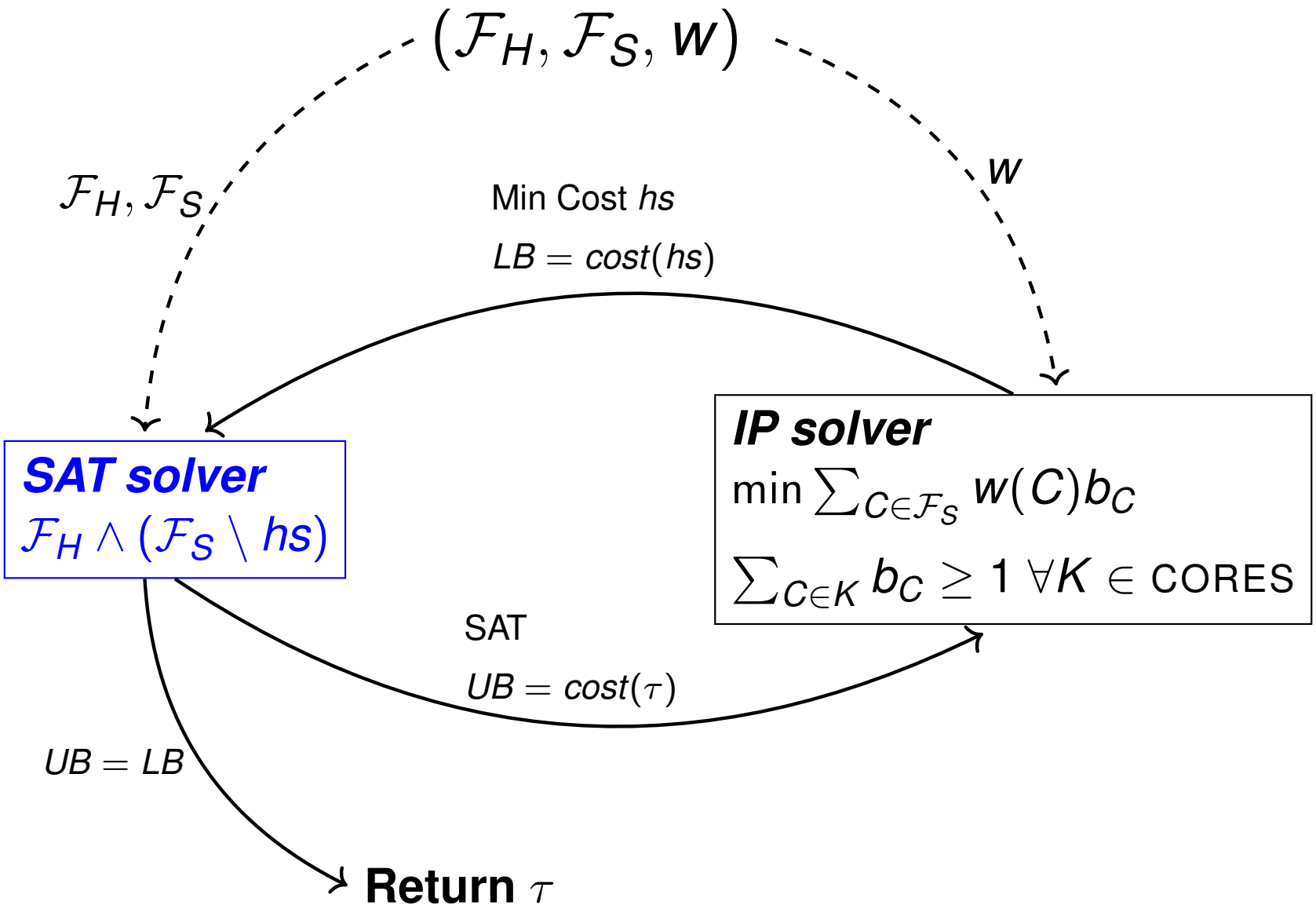

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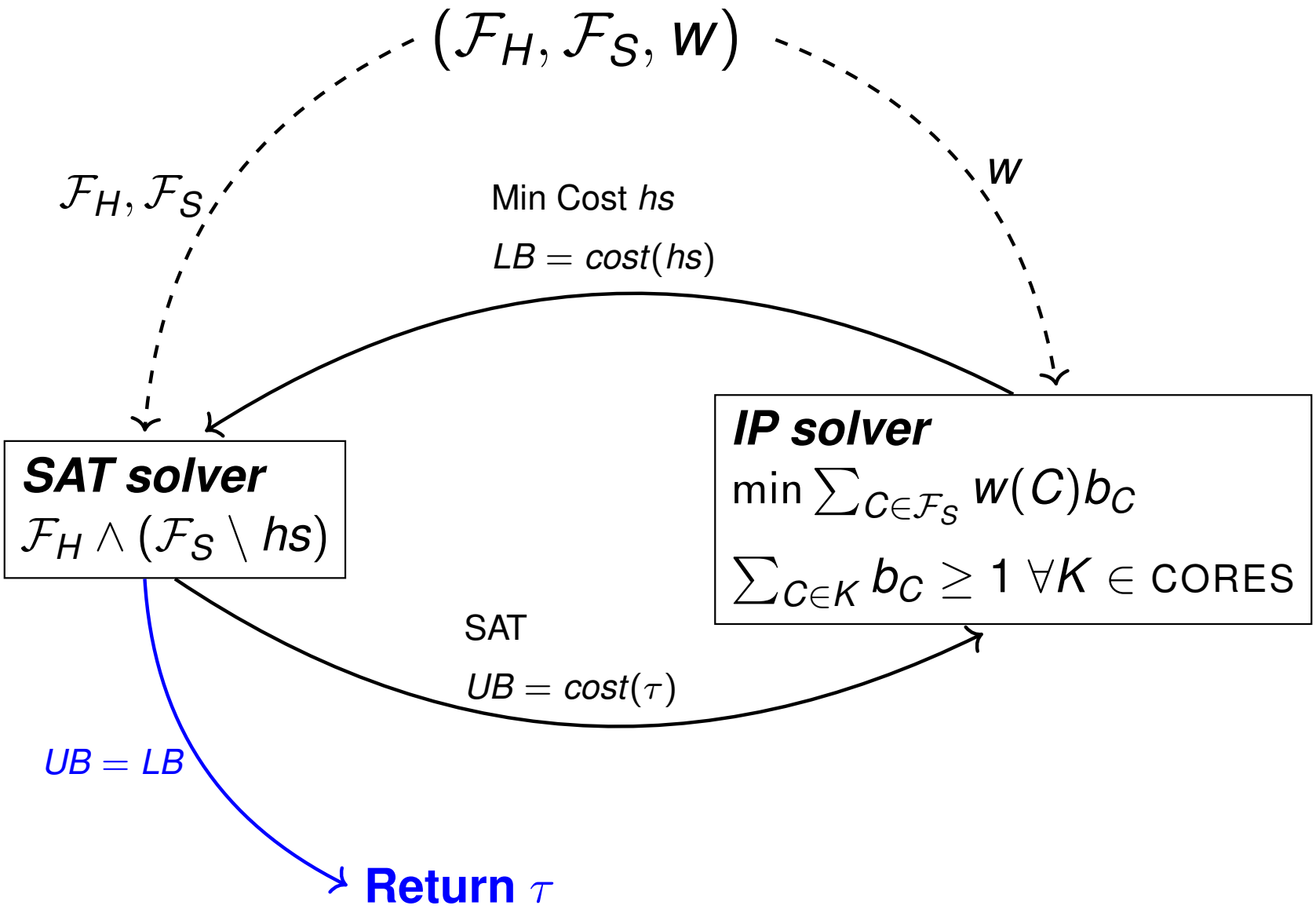

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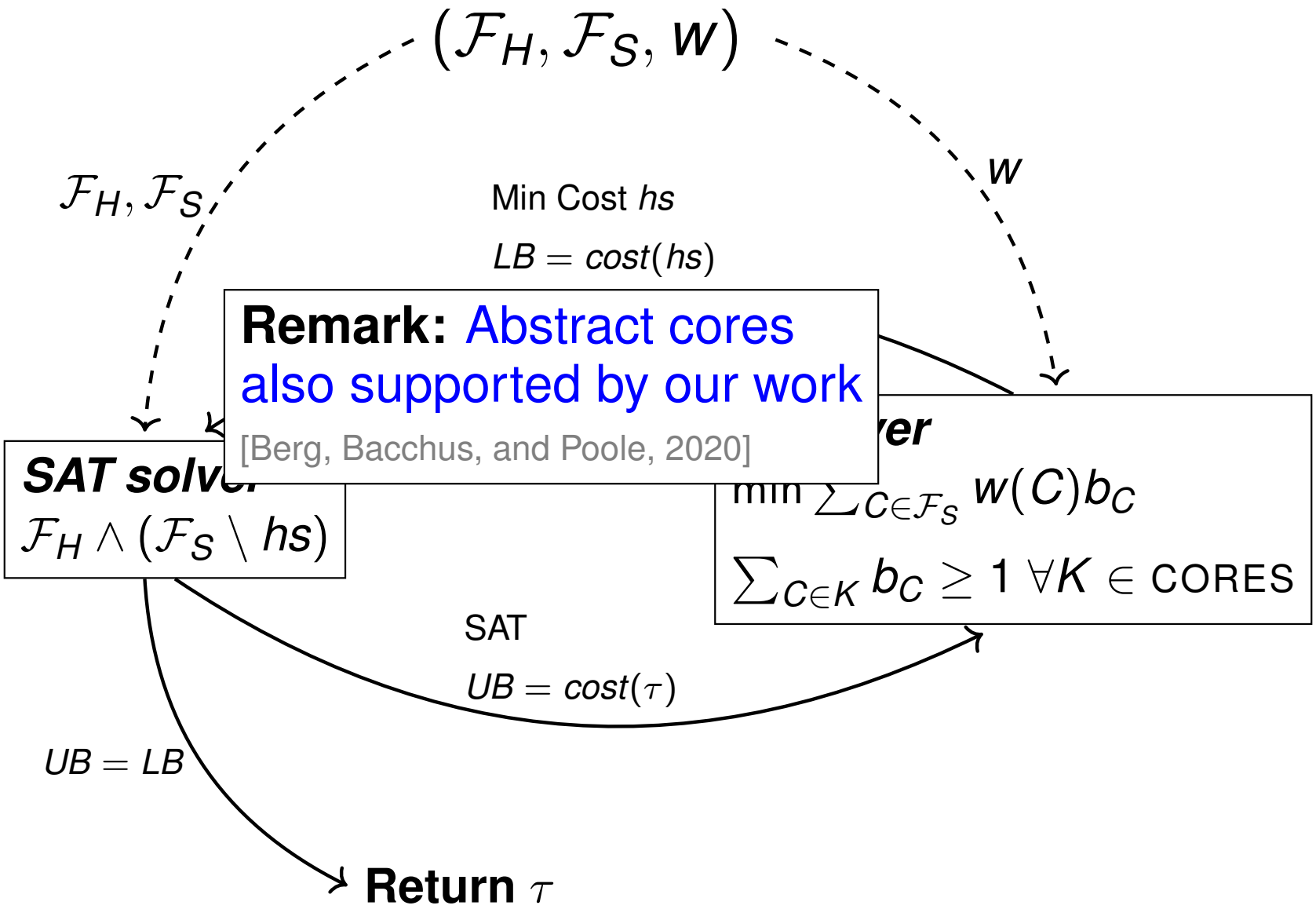

Towards Incrementality

Incremental Solving

Changing weights

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Focus of our work — incremental weight changes

Iteratively compute optimal solutions to instances with the same constraints but different weights.

The ”naive” solution: NON-INC

Independently invoke an IHS MaxSAT solver on each instance.

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Observations:

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Incremental IHS

in theory

IHS-INC($\mathcal{F}, k$)
  CORES $\leftarrow \emptyset$
  for $i = 1, \ldots, k$ **do**
    $w =$ next-w()
    $UB \leftarrow cost(\mathcal{F}, w, \tau_{best})$
    $\tau_{best} \leftarrow$ IHS($\mathcal{F}$, CORES, UB)
    output τ_{best}

Note:

- Abstract cores need (slightly) more care
  - details in paper...

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In practice: A formula $\mathcal{F}$ is simplified to $\textsc{simp}(\mathcal{F})$ prior to search
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Removal of dublicates: $(C, w_1), (C, w_2) \in \mathcal{F}_S \rightarrow (C, w_1 + w_2) \in \text{SIMP}(\mathcal{F})_S$

Need to remember original indexes.

Contradictory softs: $((x), w_1), ((\neg x), w_2) \in \mathcal{F}_S \rightarrow \begin{cases} ((x), w_1 - w_2) \in \text{SIMP}(\mathcal{F})_S \\ \text{if } w_1 > w_2 \\ ((\neg x), w_2 - w_1) \in \text{SIMP}(\mathcal{F})_S \\ \text{else.} \end{cases}$

Need to remember reification variables and change if needed.

$\vdots$

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Hardening: $(C, w_1) \in \mathcal{F}_S \quad \exists cost(\tau) < w_1 \rightarrow C \in \text{SIMP}(\mathcal{F})_H$

Can not (yet) be used in the incremental setting.

Reduced cost fixing: [Bacchus, Hyttinen, Järvisalo, and Saikko, 2017]

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Case Studies

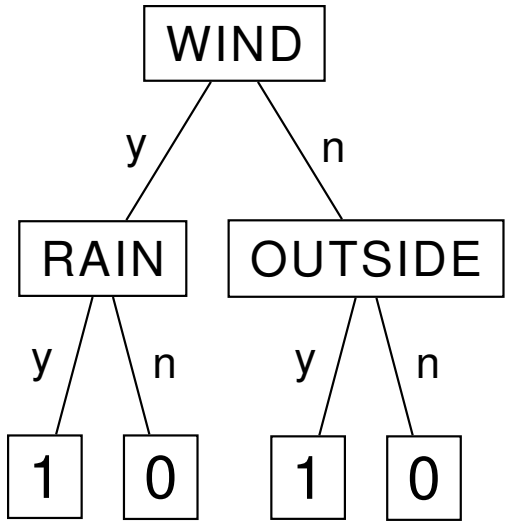
Learning (boosted) decision trees

[Narodytska, Ignatiev, Pereira, and Marques-Silva, 2018; Hu, Siala, Hebrard, and Huguet, 2020]

Decision Trees:

- Input:
  - Examples and their classes
  - Max depth U
- Learn tree $\mathcal{T}$ s.t:
  - $\text{DEPTH}(\mathcal{T}) \leq U$
  - $|\{e_i \mid c_i = \mathcal{T}(e_i)\}|$ is maximized.

Ex.	RAIN	WIND	OUTSIDE	c_i	$\mathcal{T}(e_i)$
e_1	yes	no	yes	0	1
e_2	yes	yes	yes	1	1
e_3	no	yes	yes	0	0
e_4	yes	no	no	1	0



Incrementality: AdaBoost

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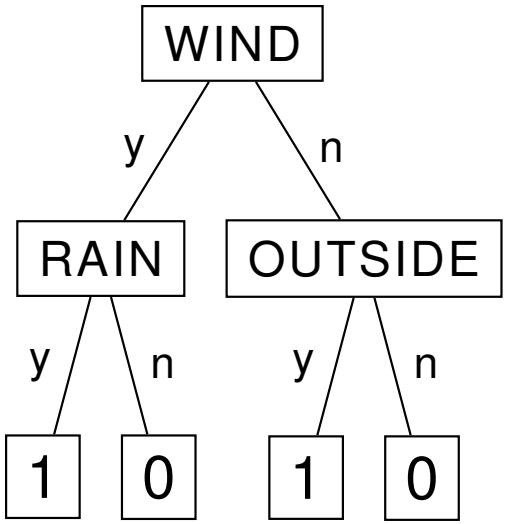

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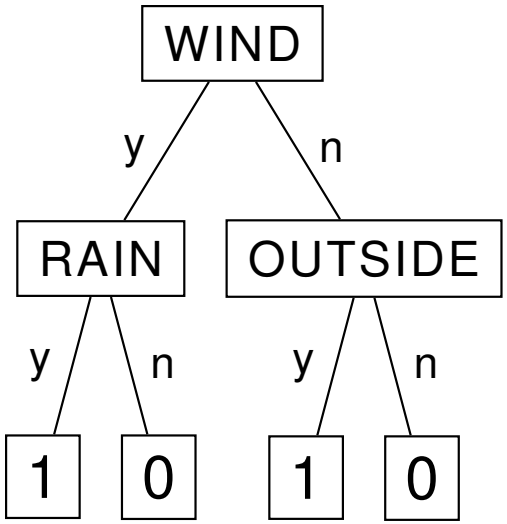
[Narodytska, Ignatiev, Pereira, and Marques-Silva, 2018; Hu, Siala, Hebrard, and Huguet, 2020]

Decision Trees:

- Input:
  - Examples and their classes
  - Max depth U
- Learn tree $\mathcal{T}$ s.t:
  - $\textsc{Depth}(\mathcal{T}) \leq U$
  - $|\{e_i \mid c_i = \mathcal{T}(e_i)\}|$ is maximized.

Ex.	RAIN	WIND	OUTSIDE	c_i	$\mathcal{T}(e_i)$
e_1	yes	no	yes	0	1
e_2	yes	yes	yes	1	1
e_3	no	yes	yes	0	0
e_4	yes	no	no	1	0



Incrementality: AdaBoost

weights = priorities of examples

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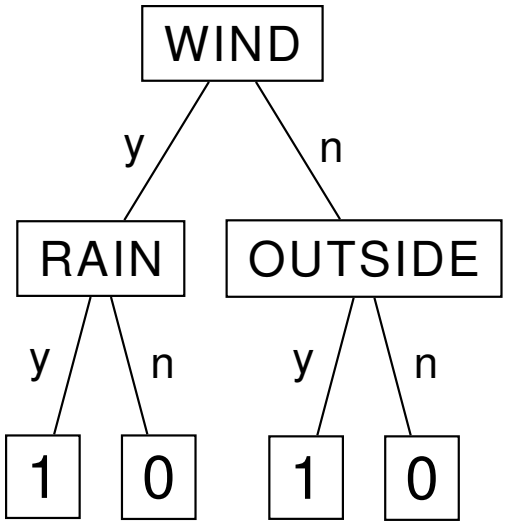
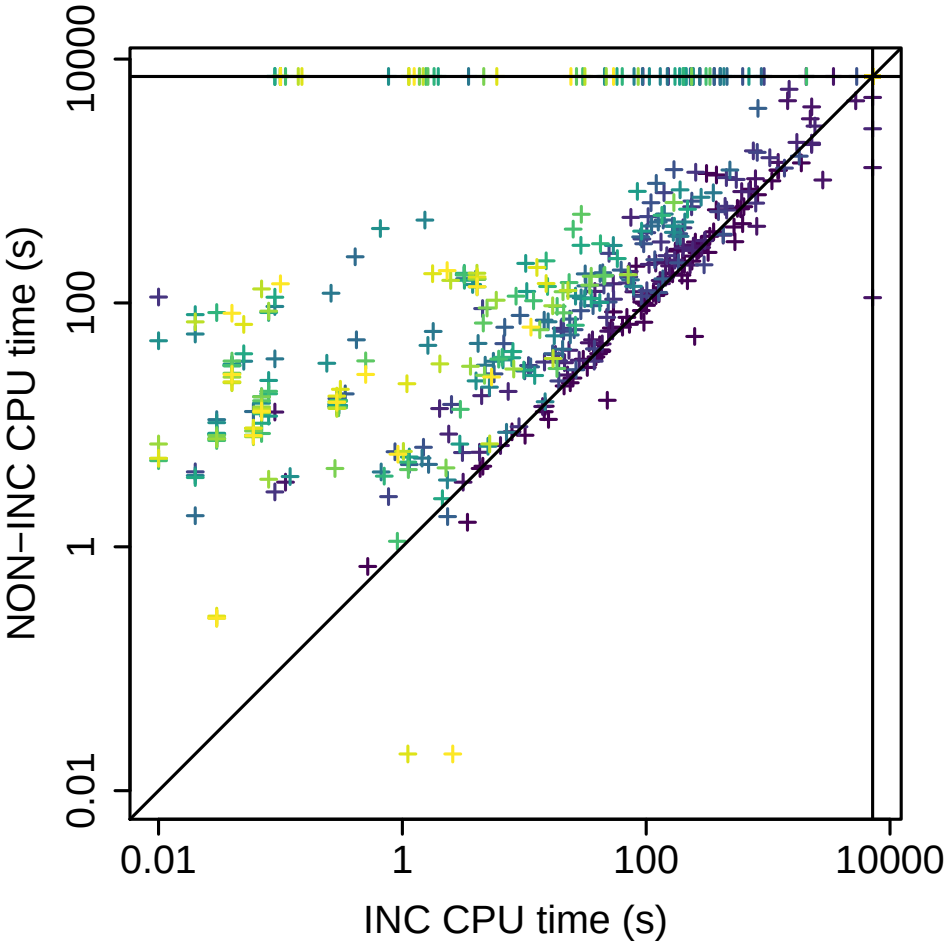
Incrementality: AdaBoost

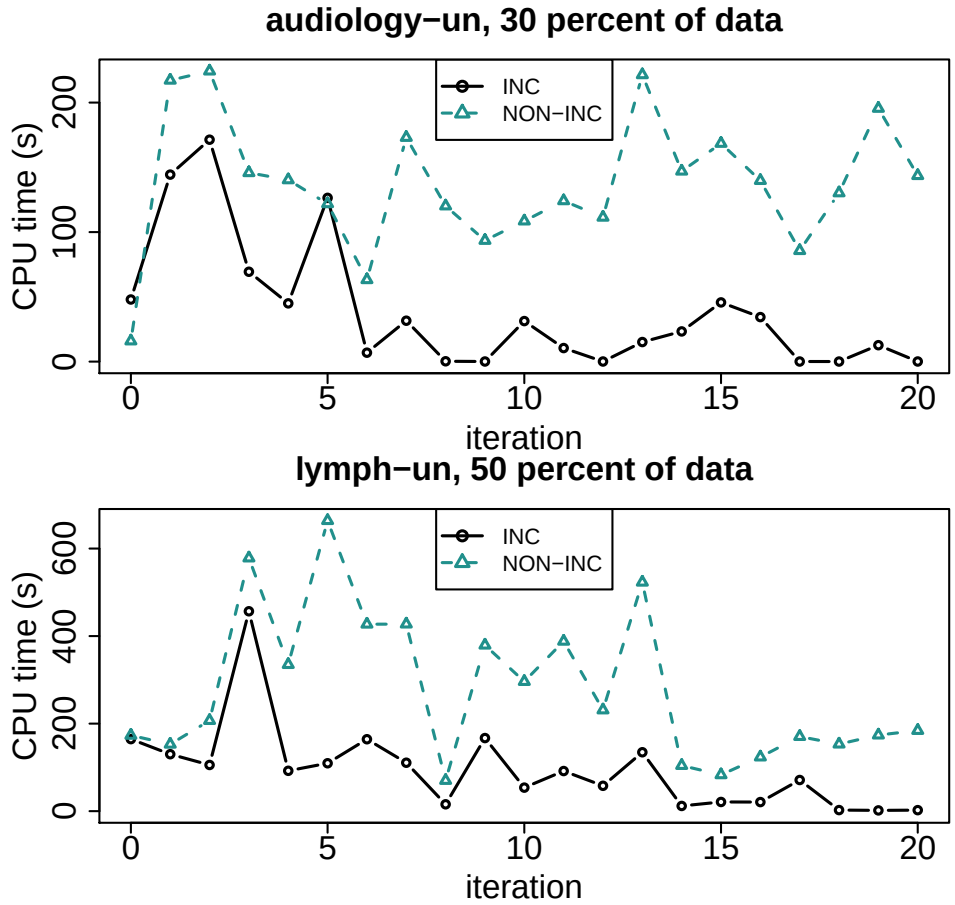
weights $=$ priorities of examples
learn diverse trees that prioritize different examples



Results

Decision Trees





Learning interpretable decision rules

[Malioutov and Meel, 2018]

Decision Rules:

- Input:
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  - integer λ
- Learn rule $\mathcal{R}$ minimizing:

$$\sum_{C \in \mathcal{R}} |C| + \lambda \cdot |\{e_i \mid c_i \neq \mathcal{R}(e_i)\}|$$

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Incrementality

λ = trade-off between interpretability and accuracy. Learn rules for different λ.

$$\mathcal{R} = (x_{\text{RAIN}}) \wedge (x_{\text{WIND}} \vee x_{\text{OUTSIDE}})$$

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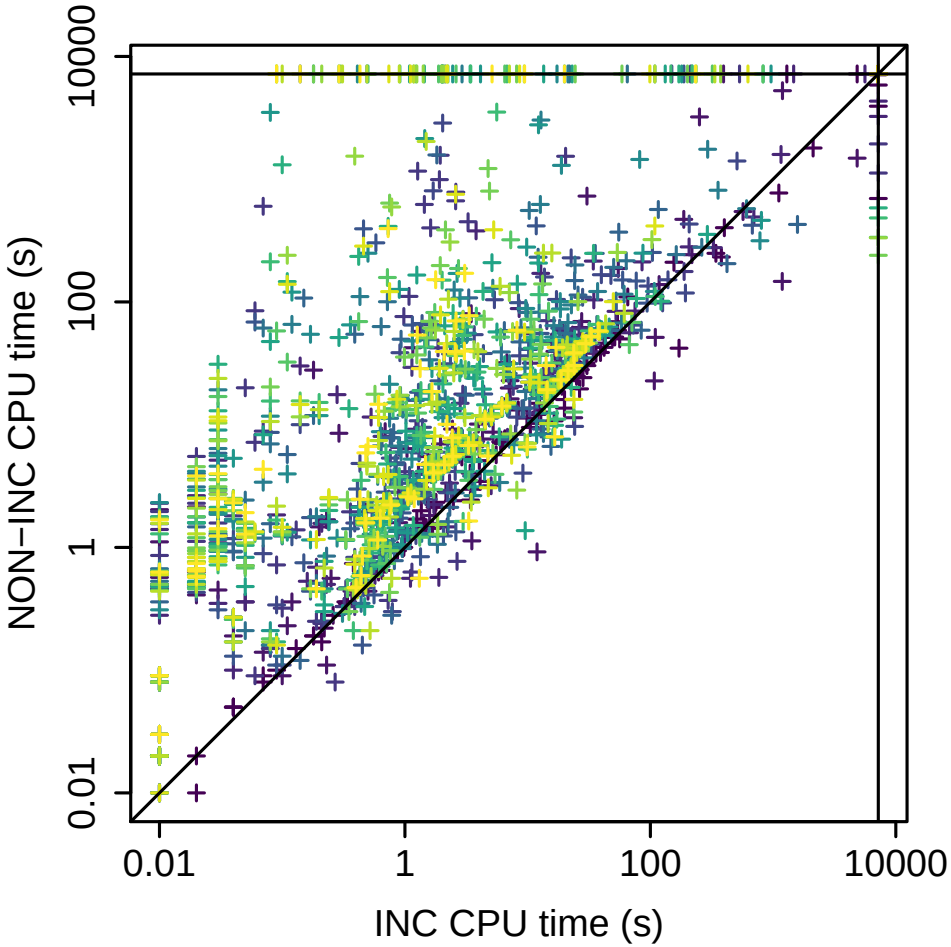

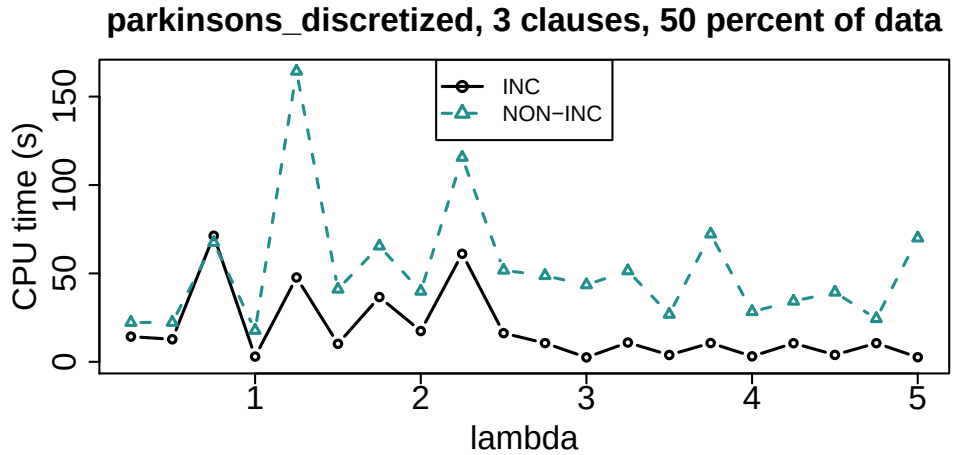

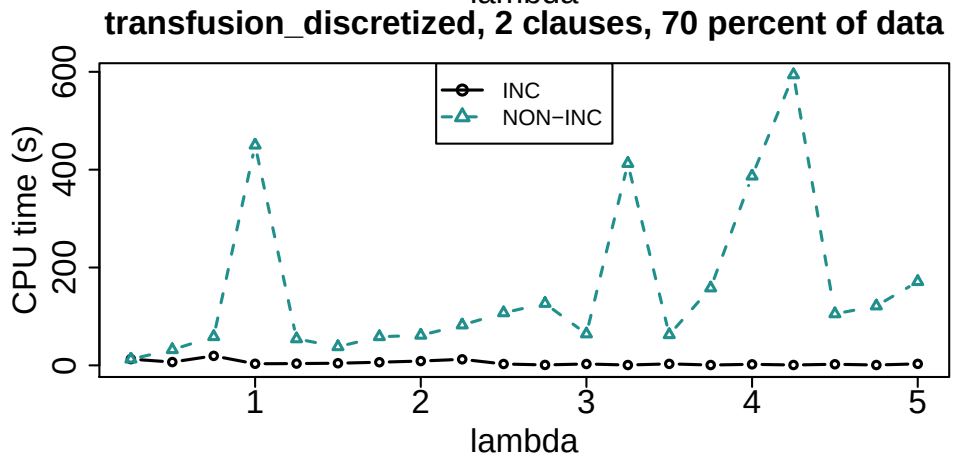

Results

Decision Rules

Take Home Message:
The increased performance of preserving cores far outweighs having to leave out (some) simplification techniques.

Conclusions

- Development of applications of incremental MaxSAT needs incremental solvers.
- In this paper we:
  - Extend the IHS MaxSAT algorithm to changing weights
  - Show potential of resulting algorithm when learning interpretable classifiers.
- Future work:
  - Further forms of incrementality (e.g. assumptions)
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