GP-SAT: a Framework for Parallel SAT Solving

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Université Paris Nanterre, France

MeFoSyLoMa – March 31, 2017

Context

How does it work?

- **Input** : a boolean logic formula
- **Output** : SAT (+ solution) or UNSAT

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- **Model checking**
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SAT is **NP-complete** [Coo71]

CPU greedy + low memory consumption $\rightarrow$ parallelization.

My objective is to improve the parallelization of SAT solving.

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φ is a formula in **conjunctive normal from** (CNF).

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When is φ SAT?

- $\varphi = \mathit{true}$ iif $\forall \omega \in \varphi, \omega = \mathit{true}$
- $\omega = \mathit{true}$ iif $\exists \ell \in \omega, \ell = \mathit{true}$

Naive approach

$$\varphi = \omega_1 \wedge \omega_2 \wedge \omega_3 \wedge \omega_4 \wedge \omega_5 \wedge \omega_6$$

- $\omega_1 = \{x_1, x_2, x_3, x_4\}$
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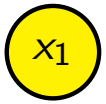

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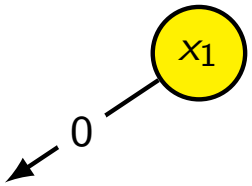

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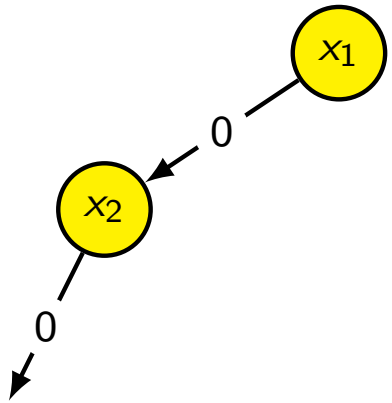

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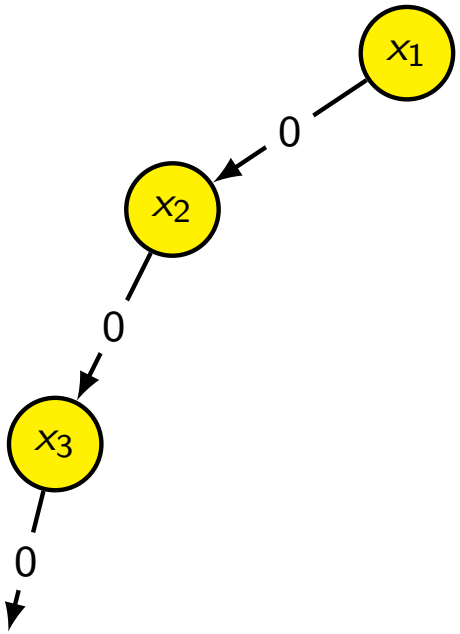

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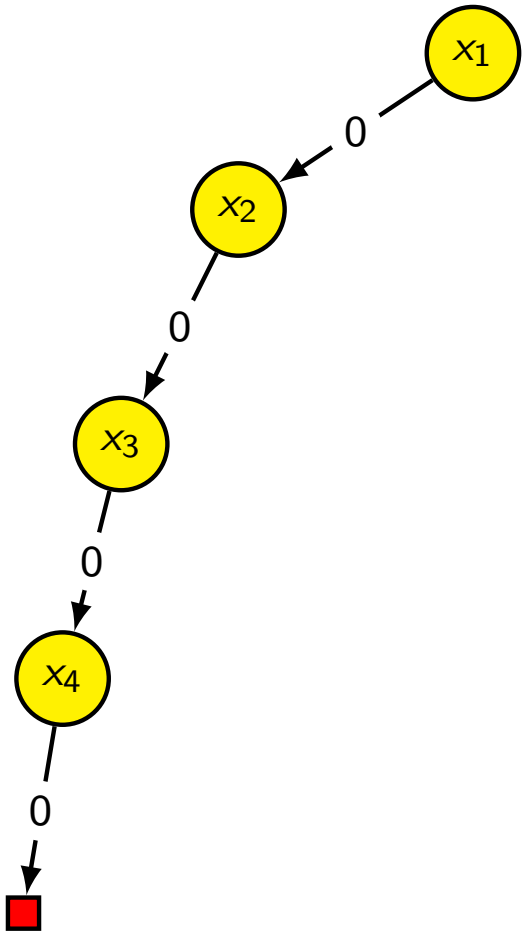

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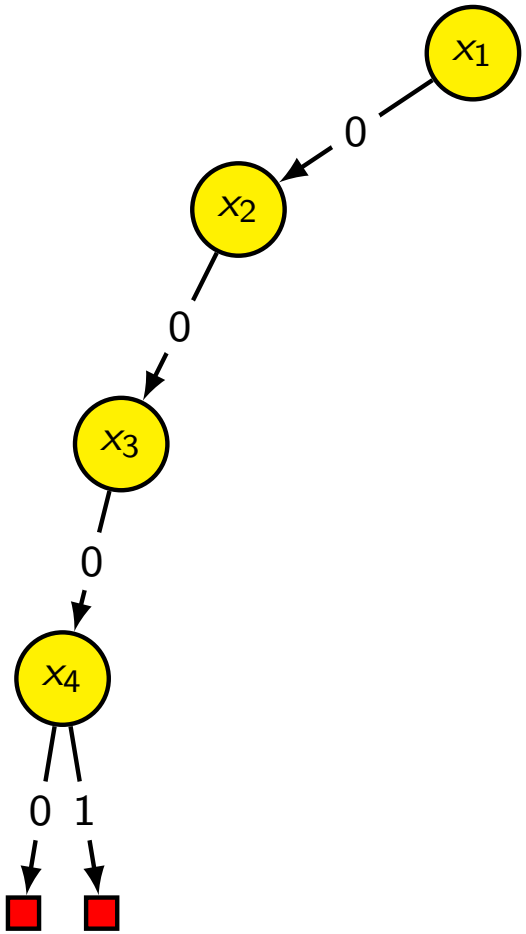

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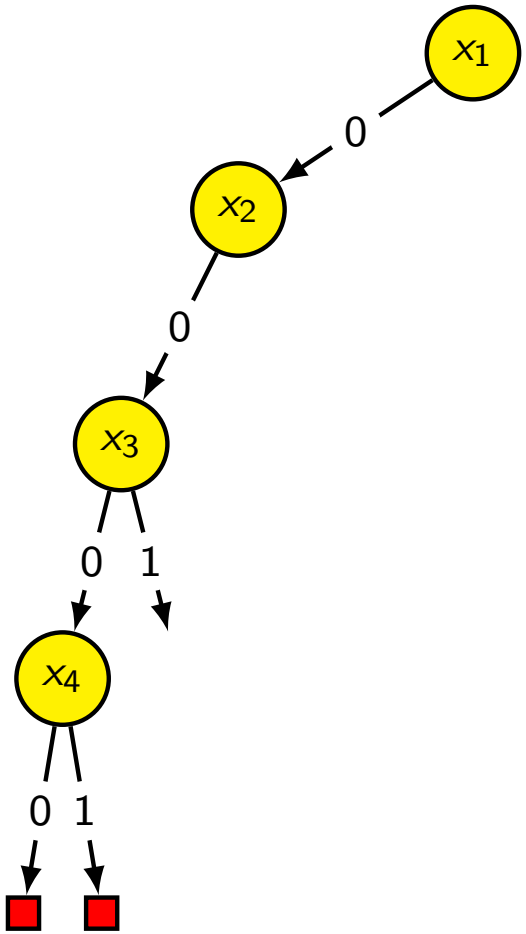

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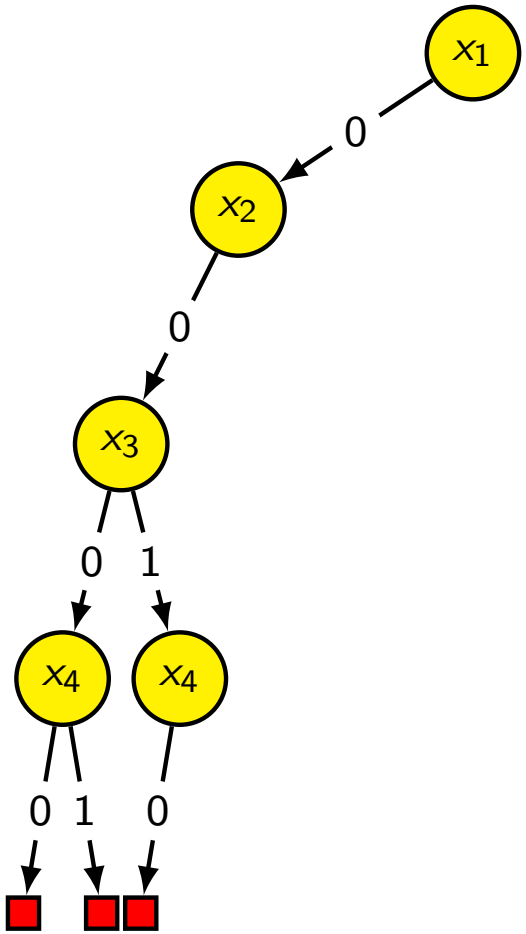

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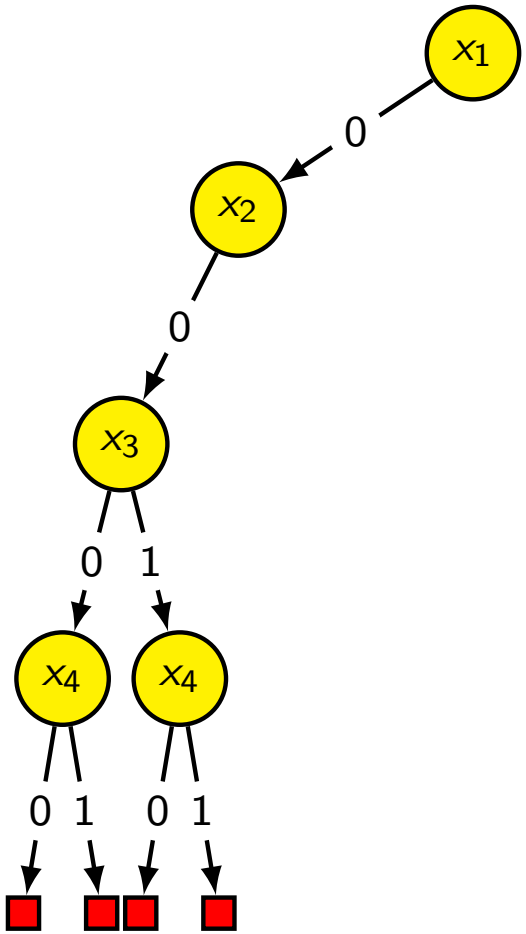

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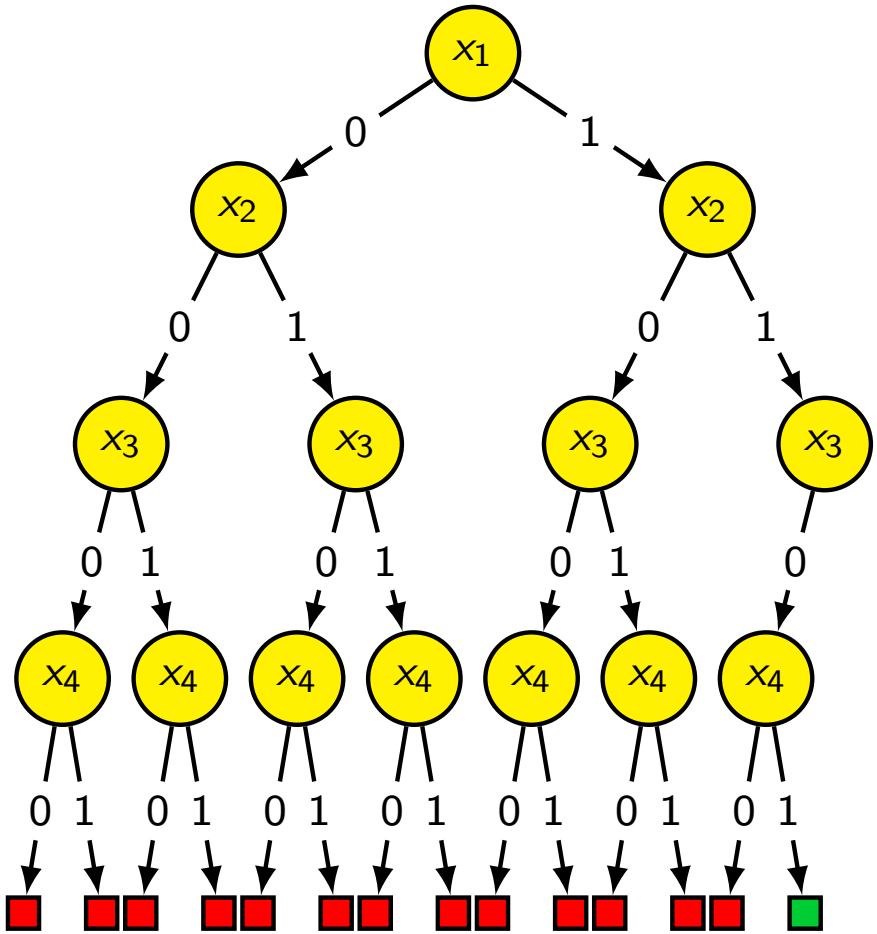

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Algorithms

- Davis, Putnam, Logemann, and Loveland (**DPLL**) [DP60, DLL62]
- Conflict Driven Clause Learning (**CDCL**) [MSS$^+$99, ZMMM01]
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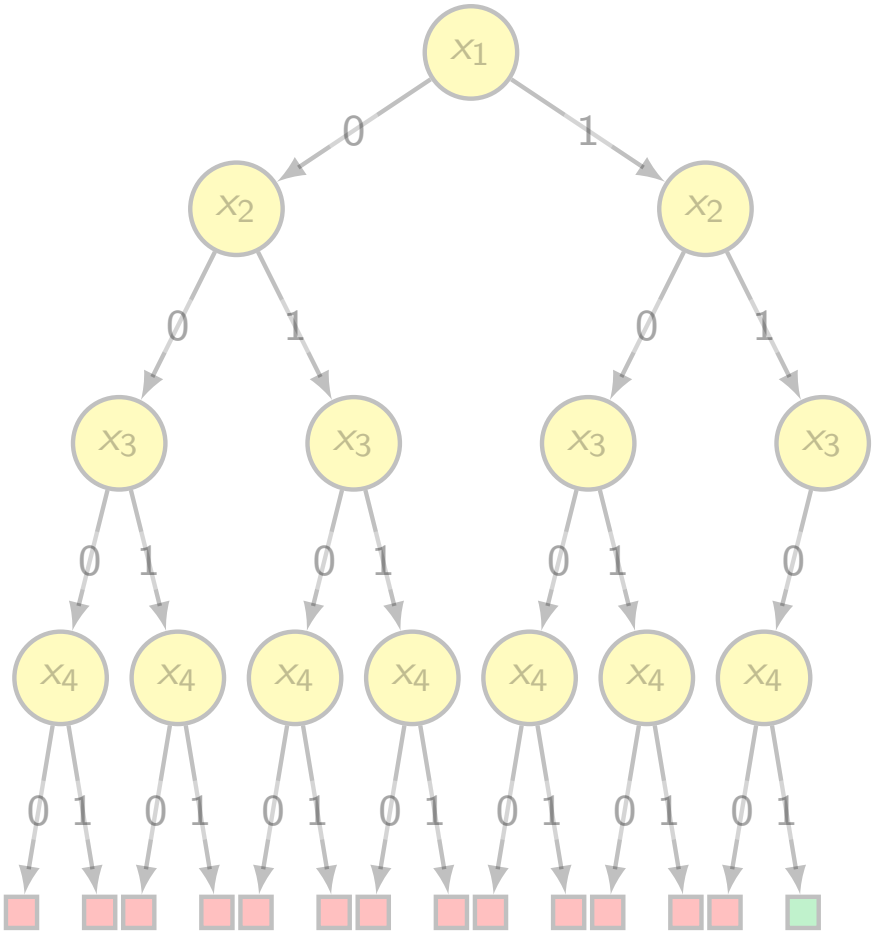
Efficiency in practice

- Unit propagation
- Decision and polarity
- Clause learning
- Restart
- Preprocessing

Unit Propagation



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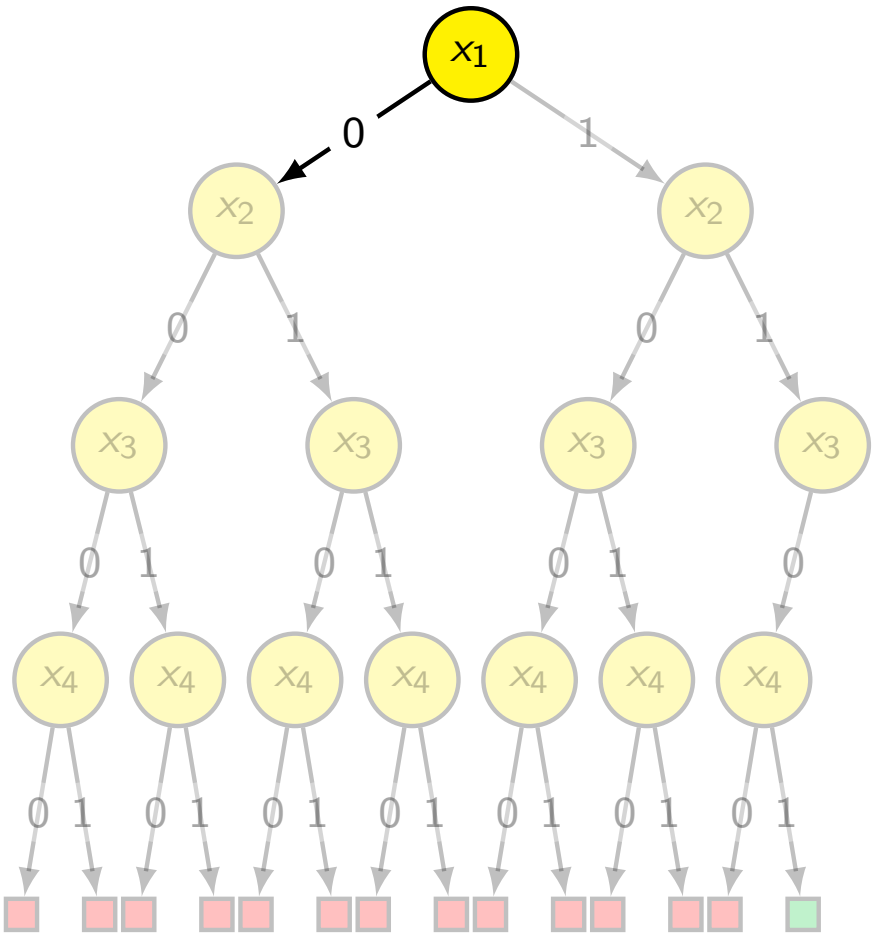

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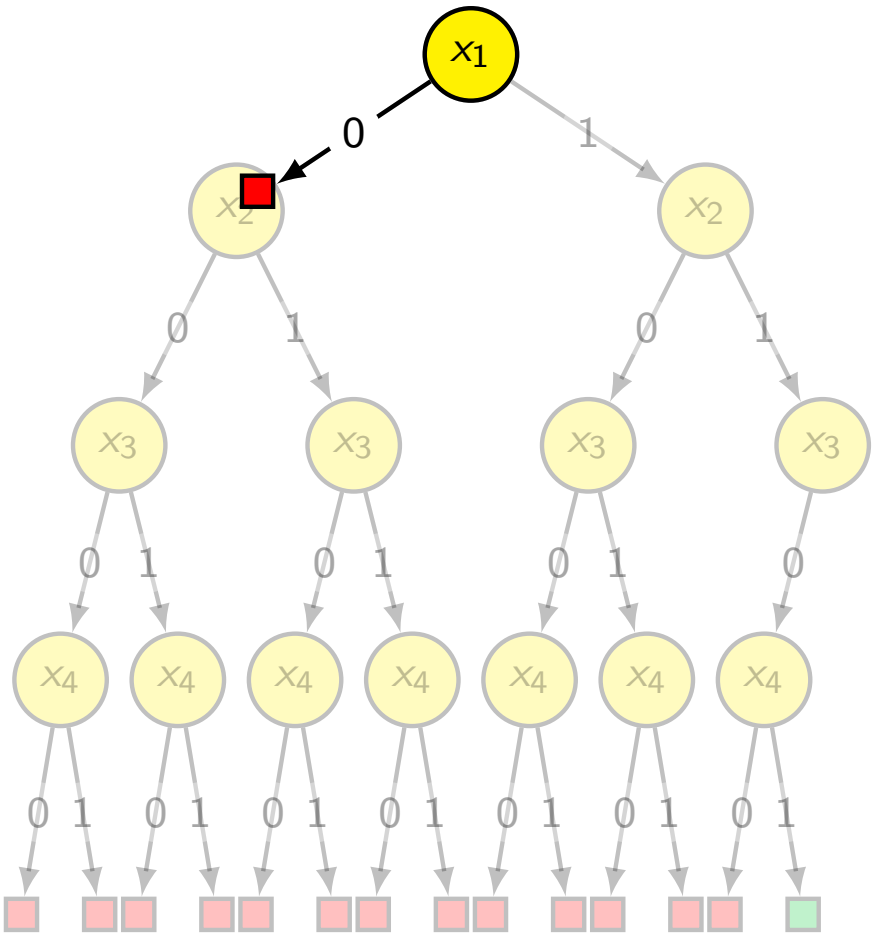

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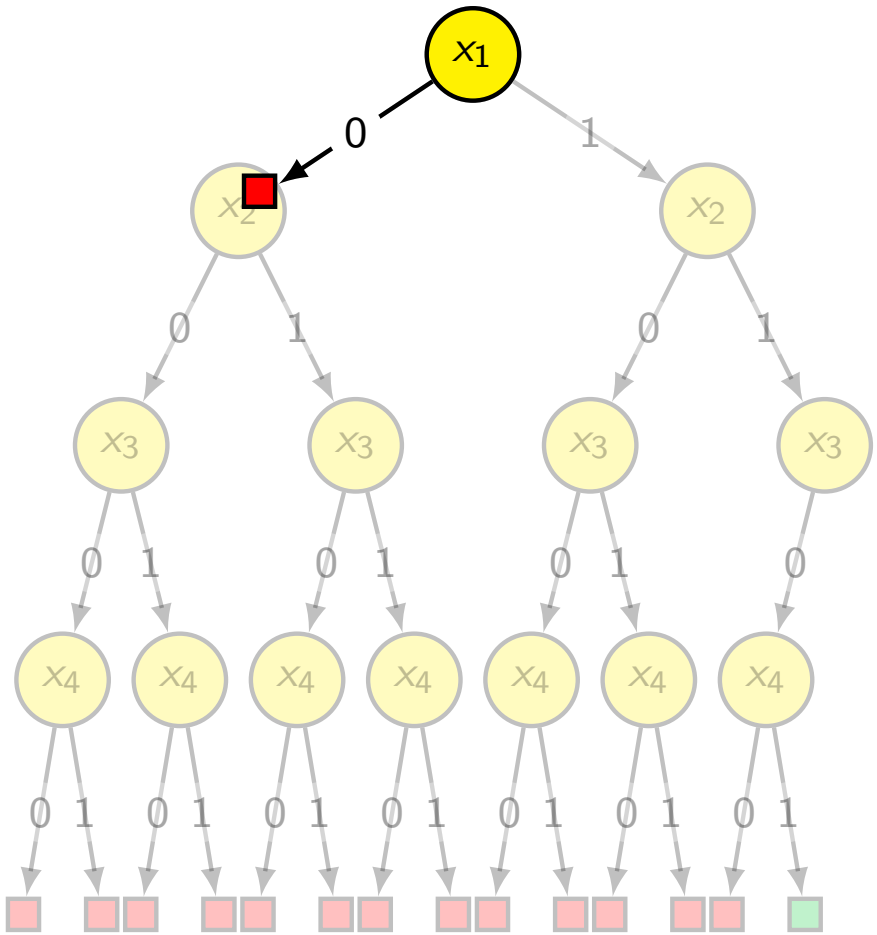
Unit Propagation & Clause Learning



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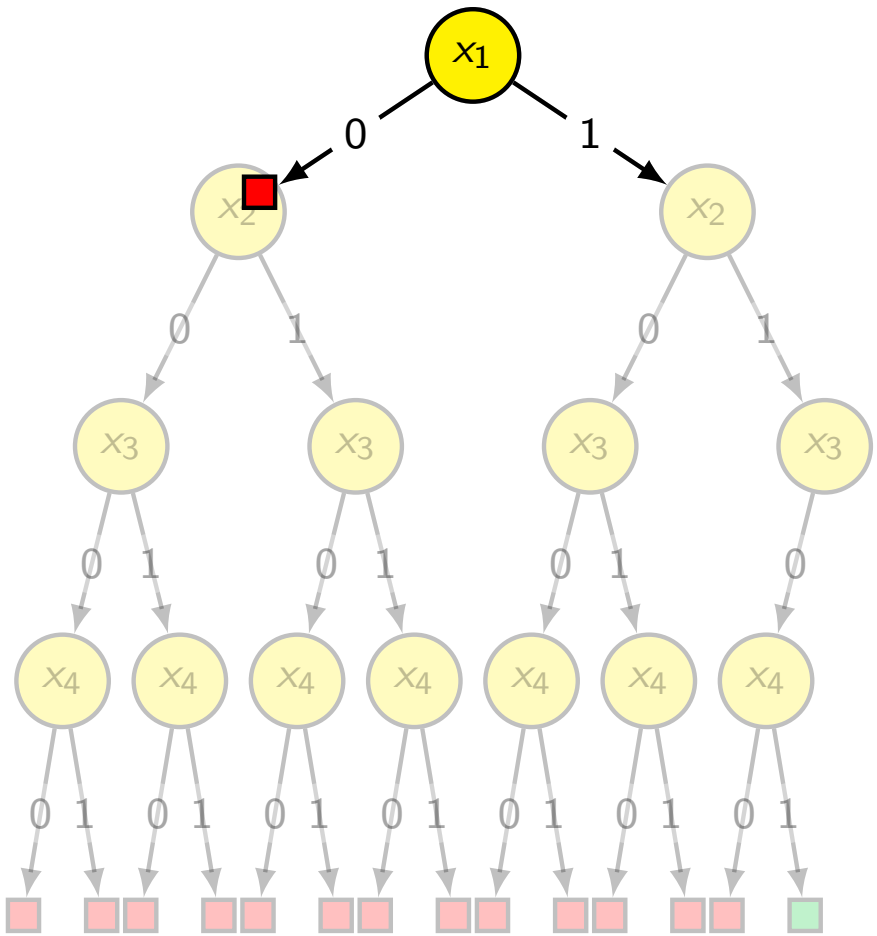

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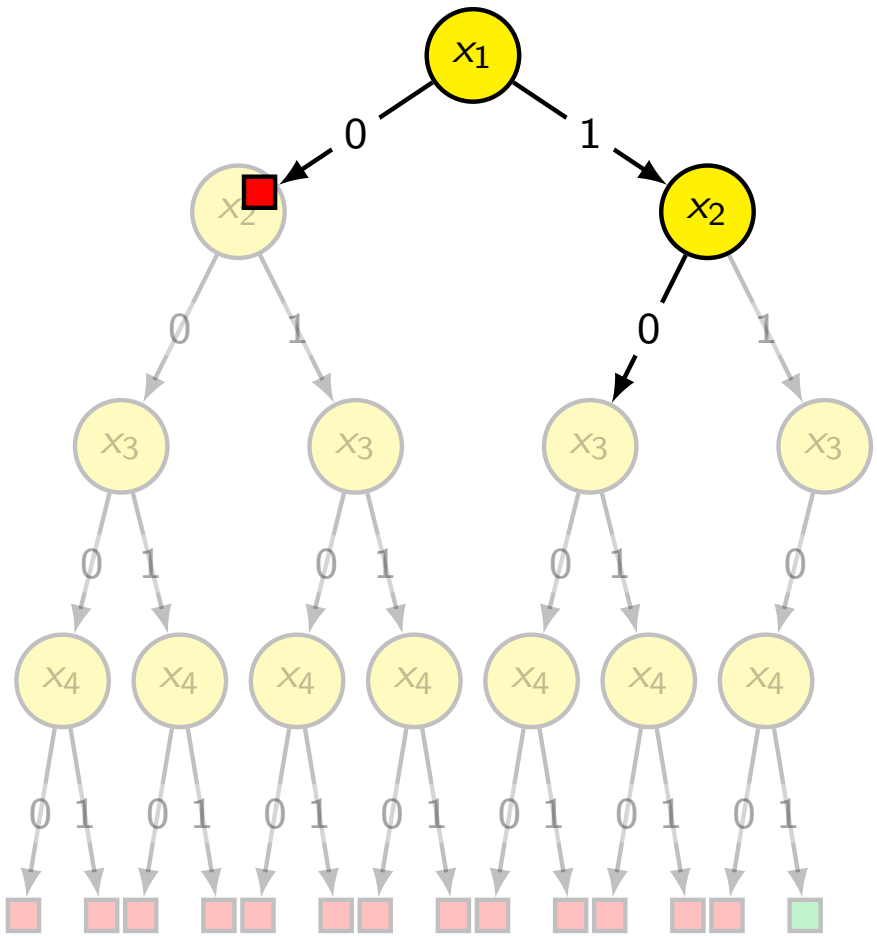

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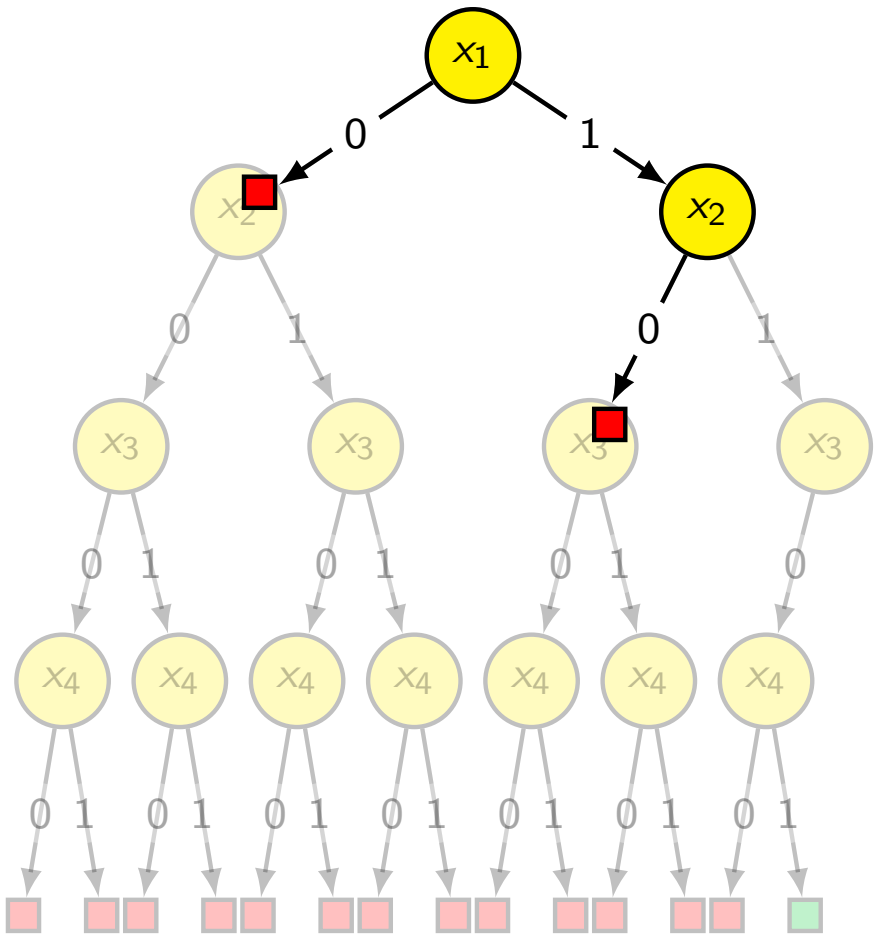

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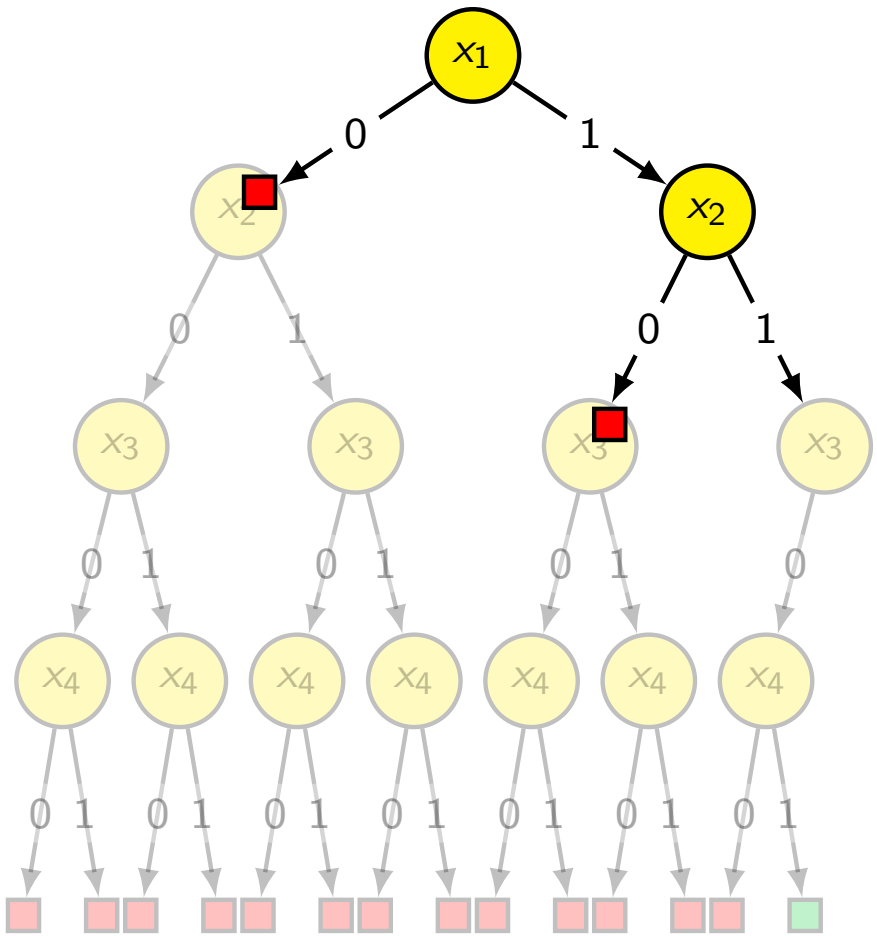

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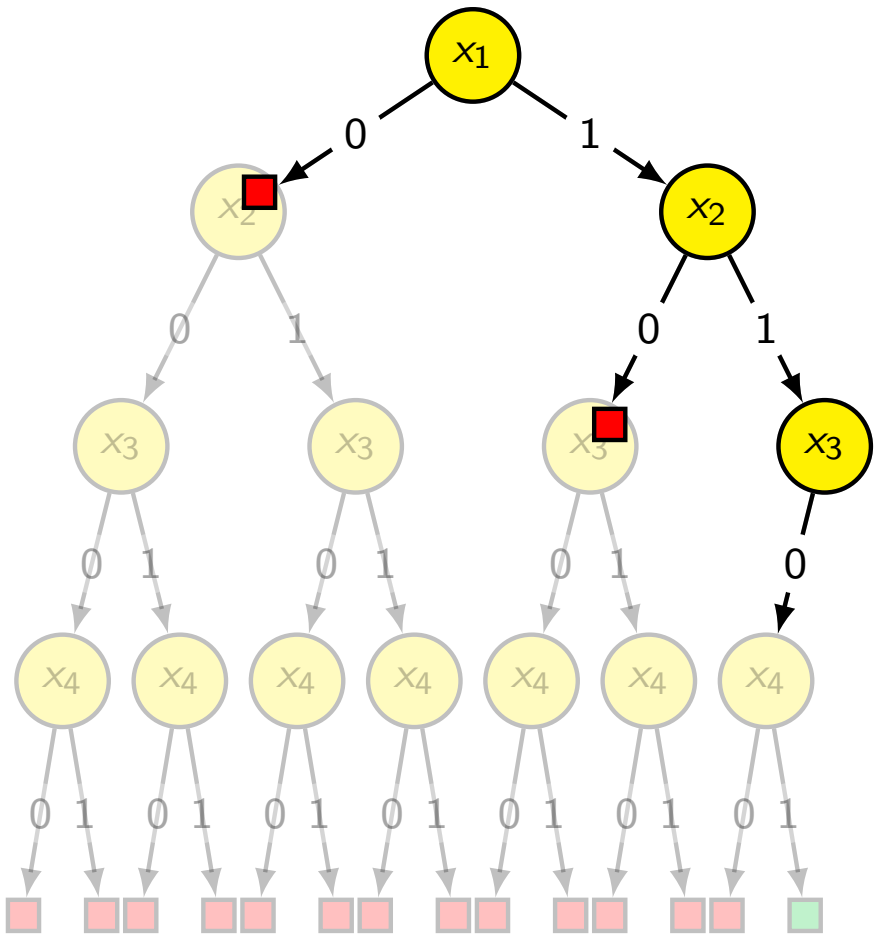

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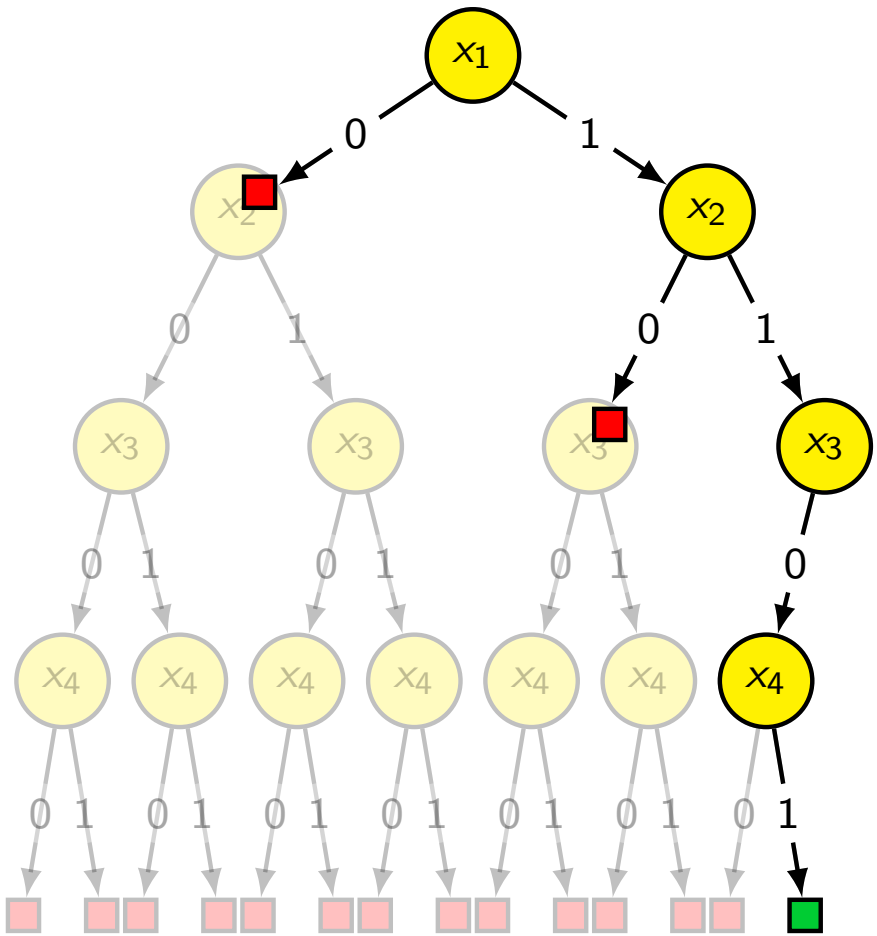

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Decision and Polarity

Decision

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2. Occurrence in smaller clauses
3. **Occurrence in conflicts**

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- **Phase saving** [PD07]:
  - Each assignment is stored
  - The polarity used is the one stored
  - Functions as a cache

Parallel Resolution

Motivations

- Bigger and bigger instances
- No more faster CPU
- Multicore architectures

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State of the art solutions

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SAT Competition 2016

Rank	Name	Type
1	treengeling	DC
2	plingeling	PF
3	cmsat5_run_parallel	PF
4	glucose-syrup	PF
5	cbpenelope	PF
6	csspenelope	PF
7	penelope_48	PF
8	Priss	PF
9	tbParaGlueminisat	PF
10	gluco_par	PF
11	ampharos-sat	DC

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Portfolio & Divide and Conquer

worker: sequential solver + workflow

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Portfolio

Multiple workers competing on the entire search space [HJS09]

- Diversification and intensification

Divide and Conquer (DC)

Divide the search space during the execution [ZBH96]

- Load balancing and work stealing

Portfolio & Divide and Conquer

worker: sequential solver + workflow

Portfolio

Multiple workers competing on the entire search space [HJS09]

- Diversification and intensification

Divide and Conquer (DC)

Divide the search space during the execution [ZBH96]

- Load balancing and work stealing

Criteria	**Portfolio**	**DC**
Learnt clauses exchange	possible	possible
Worker search spaces	same	different
Scalable	no*	yes
Easy to implement	yes	no

Portfolio & Divide and Conquer

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Possible contributions:

There also exist **hybrid approaches** (more complex).

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In practice not all the learnt clauses can be exchanged.

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- Adaptive thresholds for these measures [HJS11].

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- Choose workers allowed to communicate [LHJS12].

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Possible contributions:

Which clauses should be exchanged? And between which workers?

Difficulties Faced by Contributions

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Problem 3

- An implementation $\rightarrow$ single composition policy
- New heuristic $\times$ other mechanisms $\rightarrow$ difficult

Example of using GP-SAT

A **generic**, **modular**, and **efficient** framework to build parallel SAT solvers.

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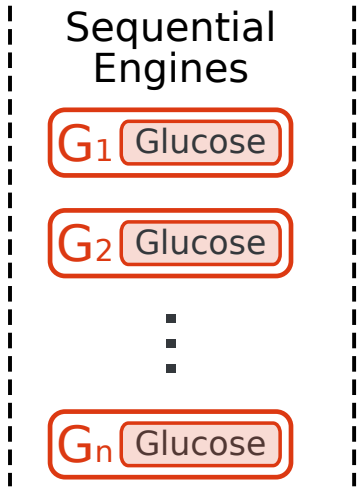

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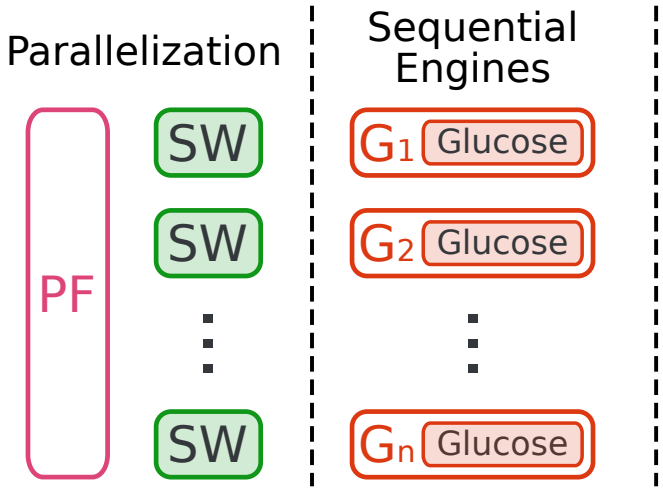

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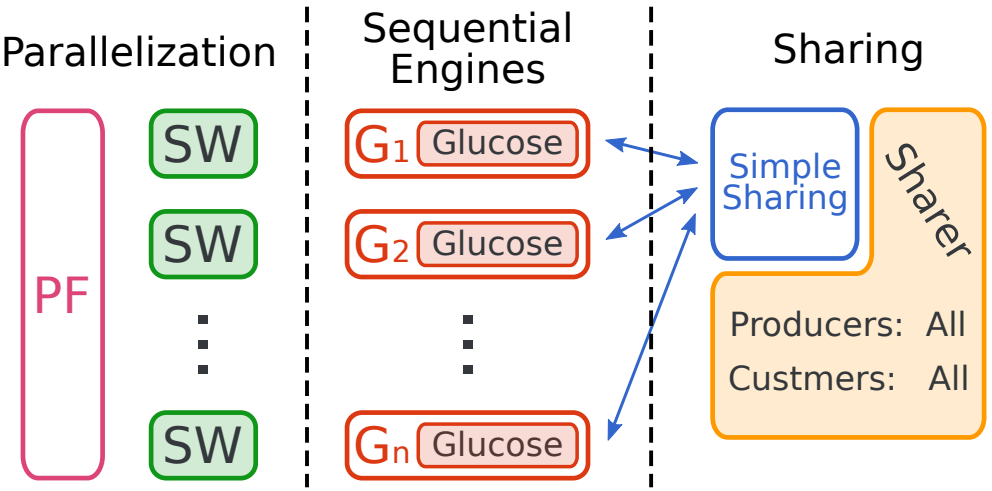
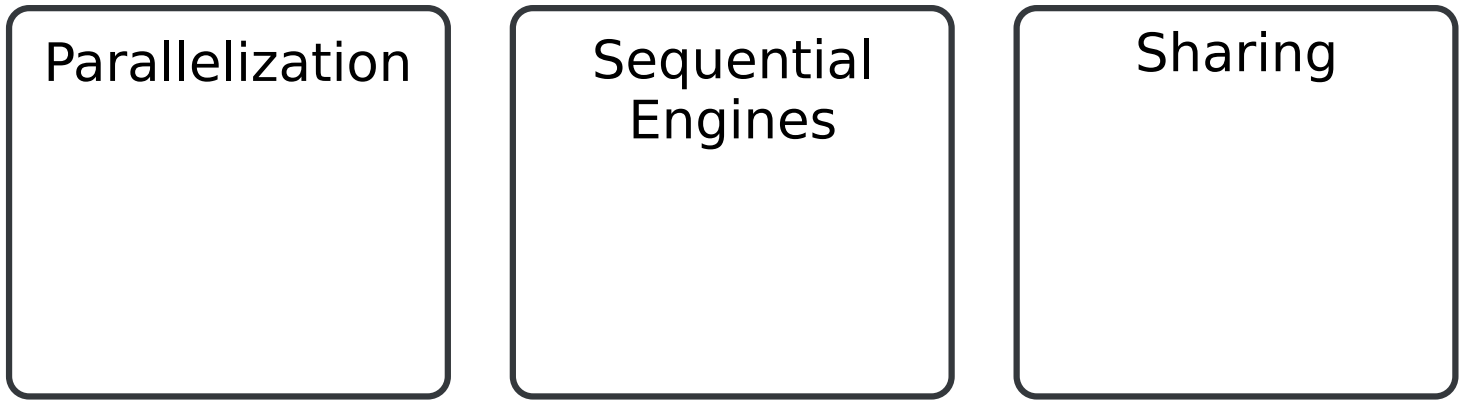


Architecture of GP-SAT



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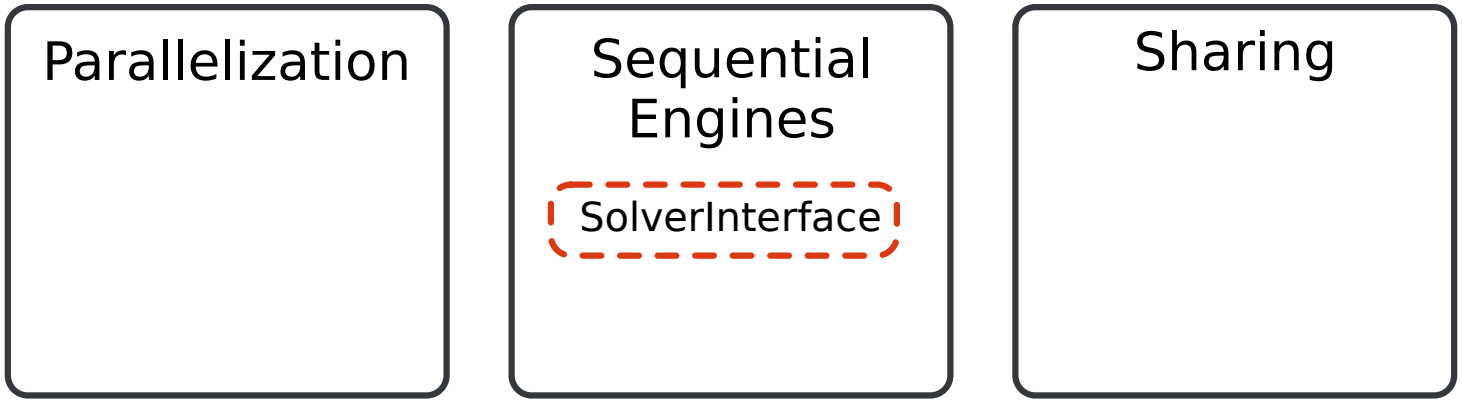

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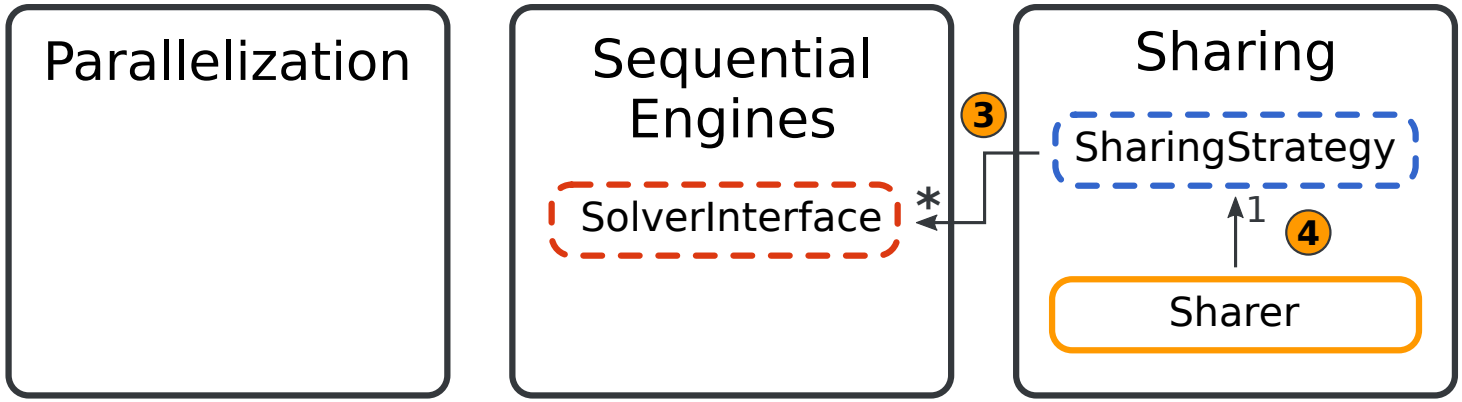

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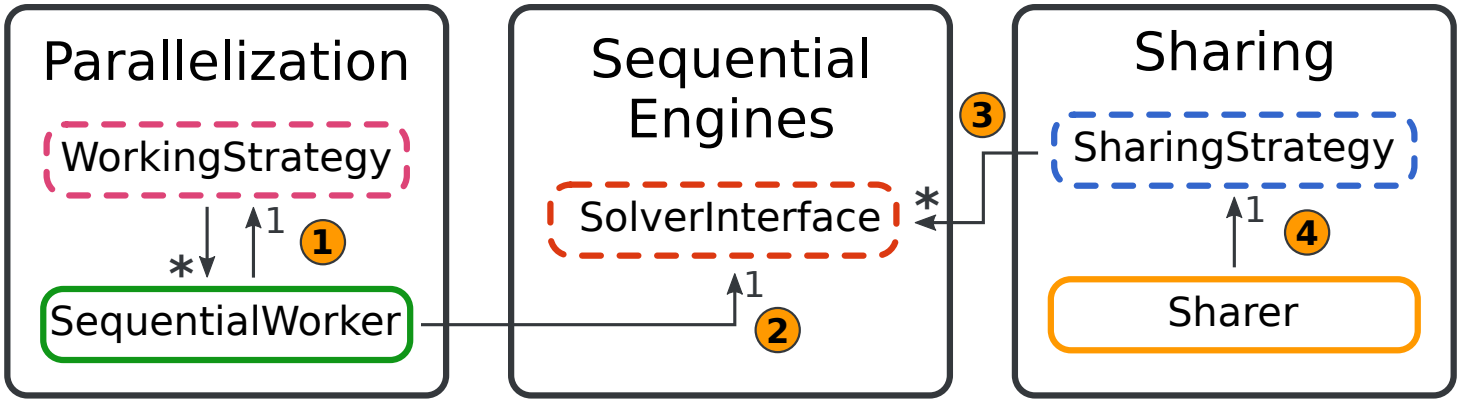

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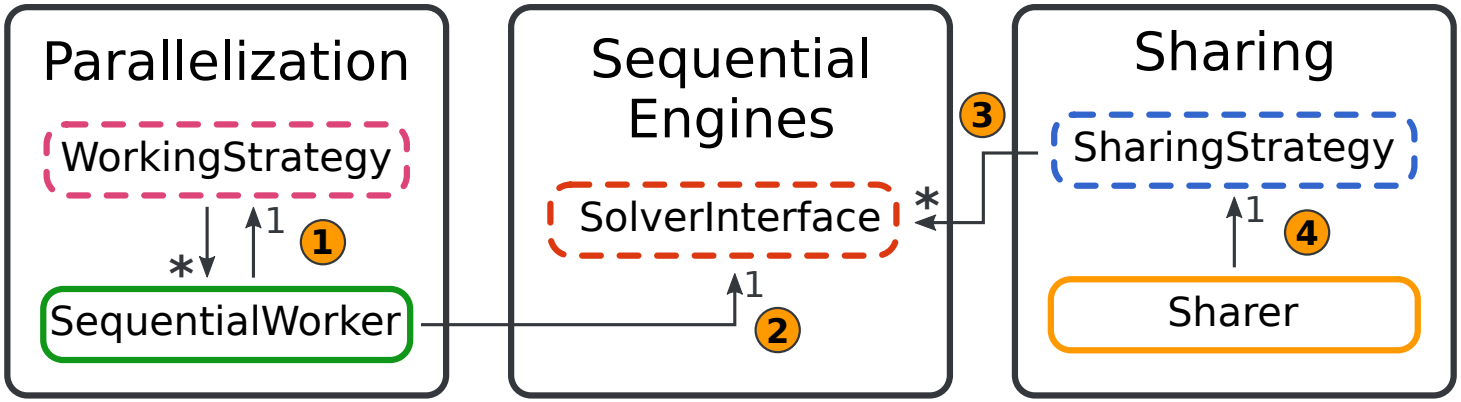

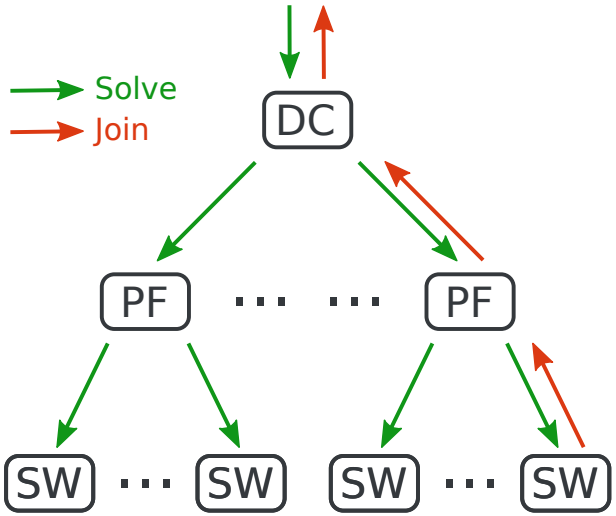

Exemple of a Divide-and-Conquer of Portfolio.

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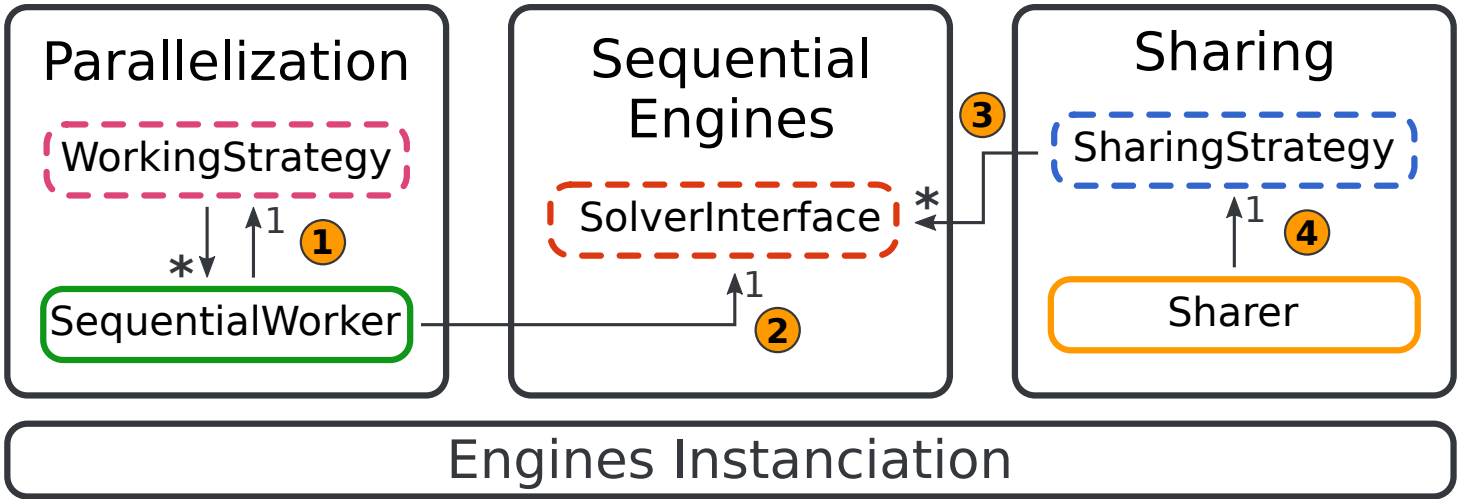

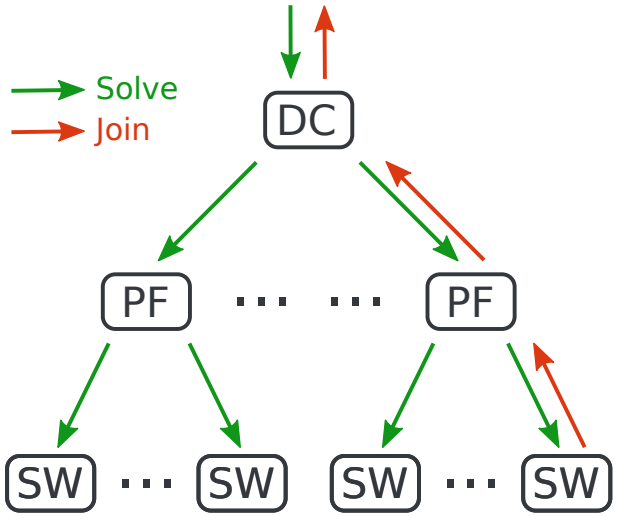

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Others Implentations using GP-SAT

- `Hordesat` [BSS15]: `Lingeling` [Bie16] + Portfolio + special sharing.
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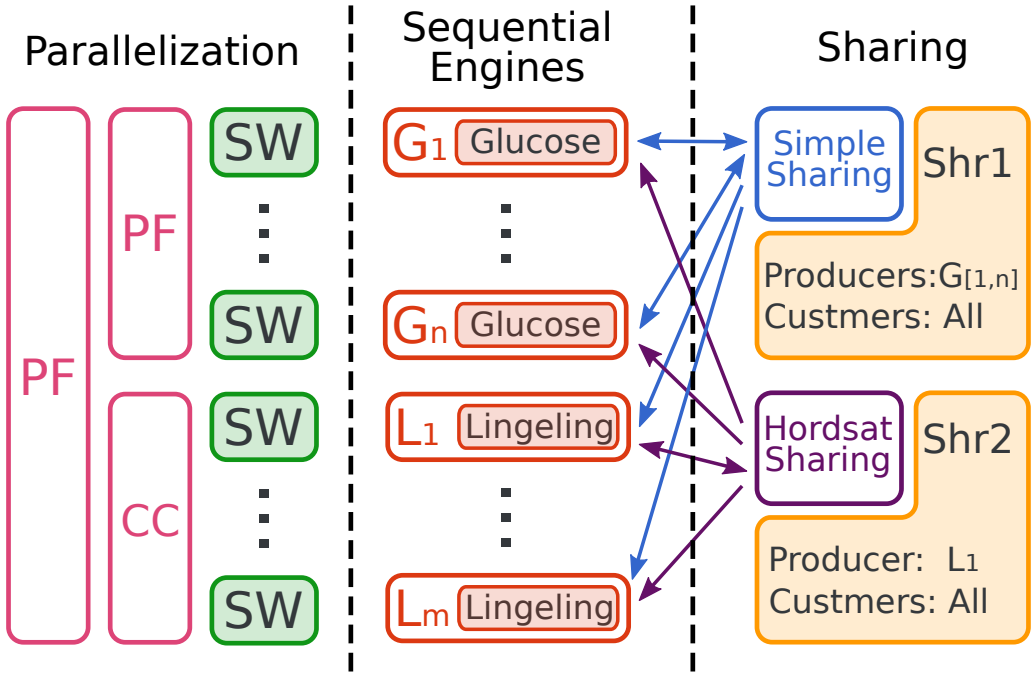
Solver mixing all the strategies.



Experiments & Results

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40 **processors:**	Intel Xeon E7-2860
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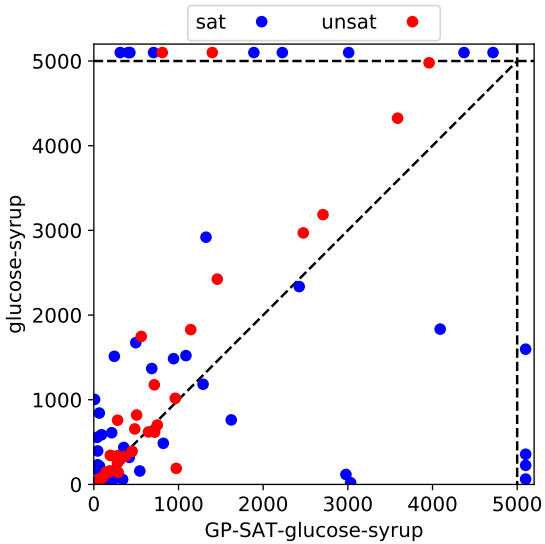

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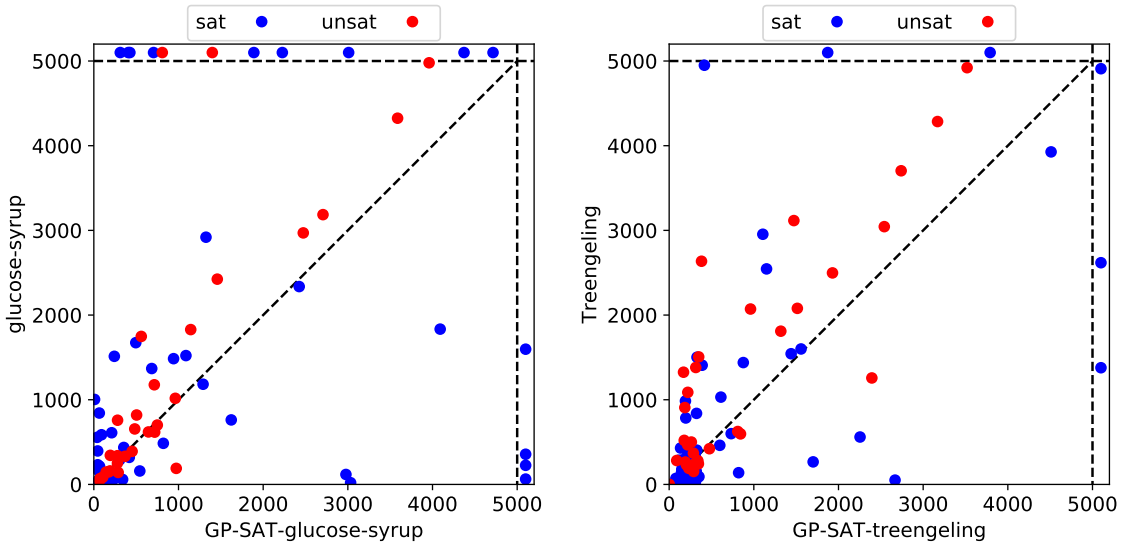

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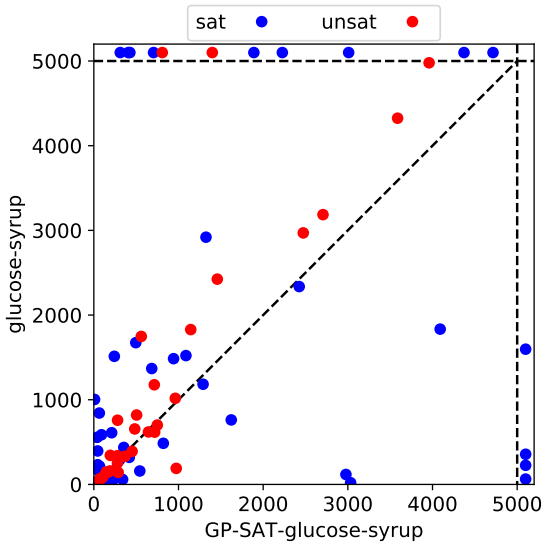

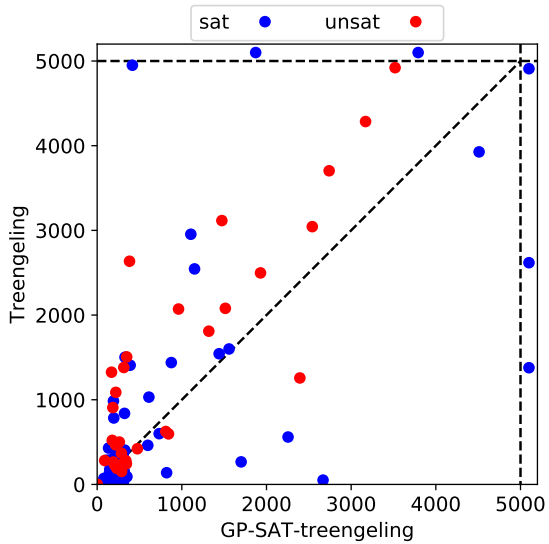

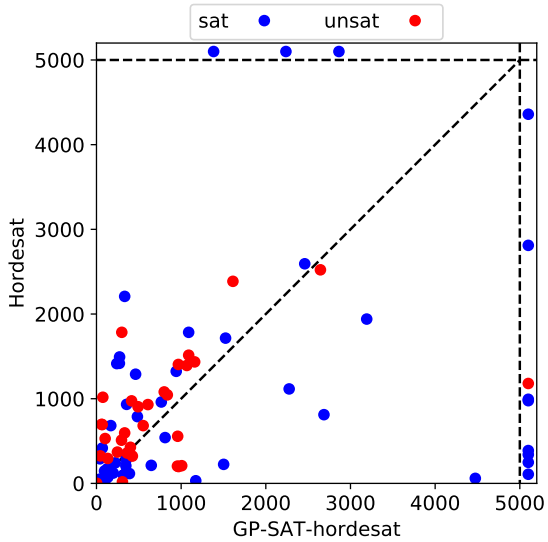

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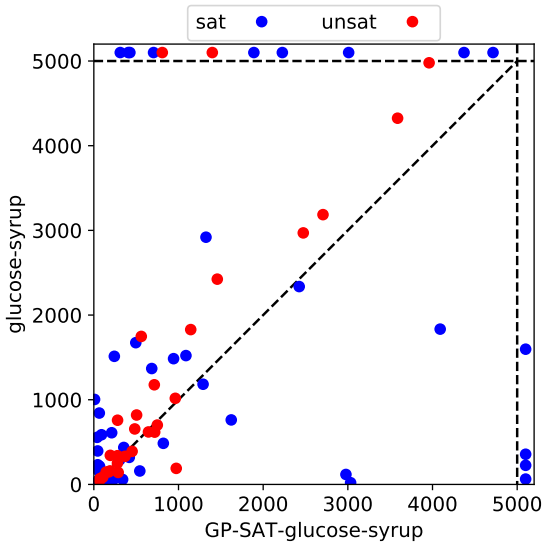

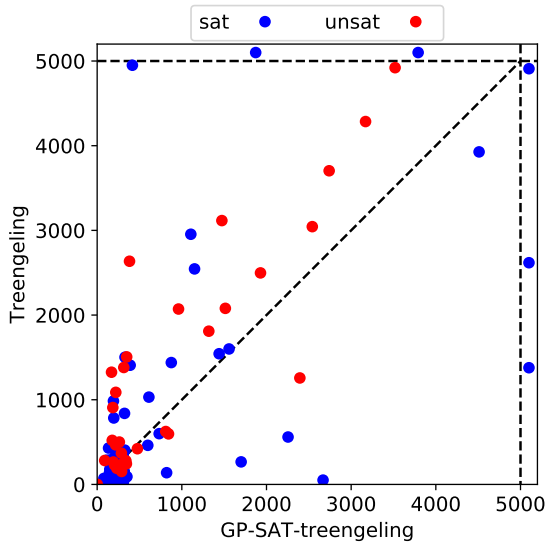

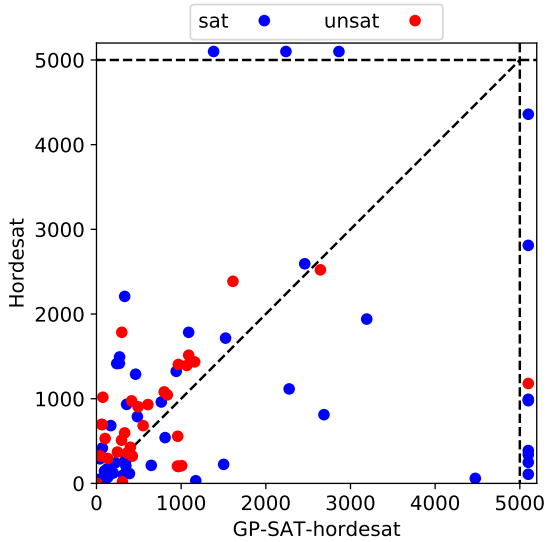

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- Bench with more instances (SAT Competition 2016).
- Toward a more generic architecture.
- **Implementing more strategies to test the architecture.**
- **Participating to the SAT Competition 2017.**
- **Use GP-SAT for our own contributions.**

Thank you!


Gilles Audemard and Laurent Simon.
Predicting learnt clauses quality in modern sat solvers.
In *IJCAI*, volume 9, pages 399–404, 2009.


Gilles Audemard and Laurent Simon.
Lazy clause exchange policy for parallel sat solvers.
In *int. conf. on Theory and Applications of Satisfiability Testing*, pages 197–205. Springer, 2014.


Armin Biere, Marijn Heule, and Hans van Maaren.
Handbook of satisfiability, volume 185.
IOS press, 2009.


Armin Biere.
Splatz, lingeling, plingeling, treengeling, yalsat entering the sat competition 2016.
SAT COMPETITION 2016, page 44, 2016.


Tomáš Balyo, Peter Sanders, and Carsten Sinz.
Hordesat: A massively parallel portfolio sat solver.
In *int. conf. on Theory and Applications of Satisfiability Testing*, pages 156–172. Springer, 2015.


Stephen A Cook.
The complexity of theorem-proving procedures.
In *3rd annual ACM symposium on Theory of computing*, pages 151–158. ACM, 1971.


Martin Davis, George Logemann, and Donald Loveland.
A machine program for theorem-proving.
Commun. ACM, 5(7):394–397, July 1962.


Martin Davis and Hilary Putnam.
A computing procedure for quantification theory.
J. ACM, 7(3):201–215, July 1960.


Youssef Hamadi, Said Jabbour, and Lakhdar Sais.
Manysat: a parallel sat solver.
Journal on Satisfiability, Boolean Modeling and Computation, 6:245–262, 2009.


Youssef Hamadi, Said Jabbour, and Jabbour Sais.
Control-based clause sharing in parallel sat solving.
In *Autonomous Search*, pages 245–267. Springer, 2011.


Youssef Hamadi, Joao Marques-Silva, and Christoph M Wintersteiger.
Lazy decomposition for distributed decision procedures.
arXiv preprint arXiv:1111.0371, 2011.


Antti EJ Hyvärinen and Christoph M Wintersteiger.
Approaches for multi-core propagation in clause learning satisfiability solvers.
Technical report, Technical Report MSR-TR-2012-47, 2012.


Jia Hui Liang, Vijay Ganesh, Pascal Poupart, and Krzysztof Czarnecki.
Learning rate based branching heuristic for sat solvers.
In *Theory and Applications of Satisfiability Testing*, pages 123–140. Springer, 2016.


Nadjib Lazaar, Youssef Hamadi, Said Jabbour, and Michèle Sebag.
Cooperation control in Parallel SAT Solving: a Multi-armed Bandit Approach.
Research Report RR-8070, INRIA, September 2012.


Matthew W Moskewicz, Conor F Madigan, Ying Zhao, Lintao Zhang, and Sharad Malik.
Chaff: Engineering an efficient sat solver.
In *38th annual Design Automation Conference*, pages 530–535. ACM, 2001.


Joao P Marques-Silva, Karem Sakallah, et al.
Grasp: A search algorithm for propositional satisfiability.
IEEE Trans. on Computers, 48(5):506–521, 1999.


Knot Pipatsrisawat and Adnan Darwiche.
A lightweight component caching scheme for satisfiability solvers.
In *Theory and Applications of Satisfiability Testing–SAT 2007*, pages 294–299. Springer, 2007.


Hantao Zhang, Maria Paola Bonacina, and Jieh Hsiang.
PSATO: a distributed propositional prover and its application to quasigroup problems.
Journal of Symbolic Computation, 21(4):543–560, 1996.


Lintao Zhang, Conor F Madigan, Matthew H Moskewicz, and Sharad Malik.
Efficient conflict driven learning in a boolean satisfiability solver.
In *IEEE/ACM int. conf. on Computer-aided design*, pages 279–285. IEEE Press, 2001.

Clause Learning

Let $x_1 = 0$, $x_4 = 0$, $x_8 = 1$ be the reasons of a conflict.

$$\varphi \equiv \varphi \wedge \omega_{\text{learnt}}, \text{ where } \omega_{\text{learnt}} = \{x_1, x_4, \neg x_8\}$$

Problem

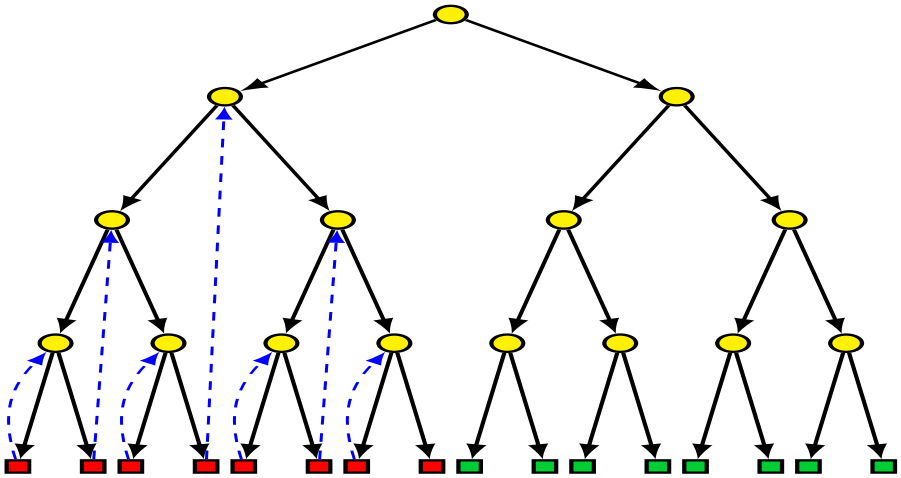
Too many clauses are learnt
$\rightarrow$ not all of them can be kept.

Selection criteria

- Activity: keep clauses used for propagation/conflict resolution.
- Size: longer clauses are less used for propagation.
- **Literal Block Distance (LBD)** [AS09]:
  - number of decision level gathered by a clause.

Restart

Motivations



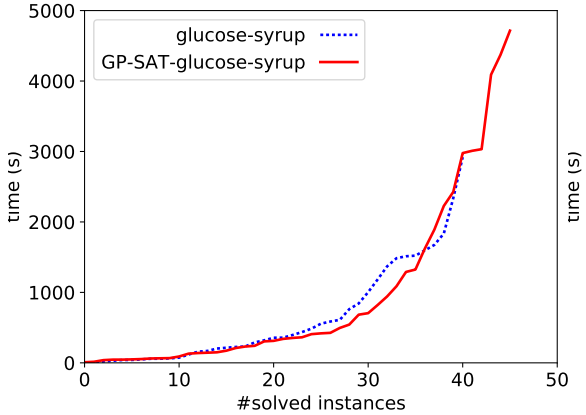
Escape from hard zones (heavy-tailed) [BHvM09].

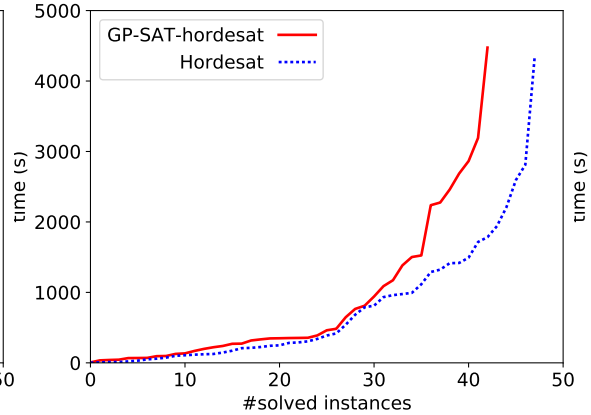
Strategies

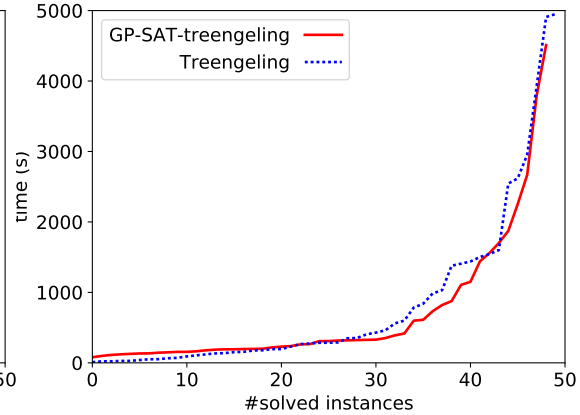
- #conflicts: arithmetic, geometric, Luby progressions.
- Progress saving: prevents from softness.
- **Average LBD**: are we in a good region for learning?
- **SAT/UNSAT**: are we close to find a solution?

Cactus Plots

sat







unsat