

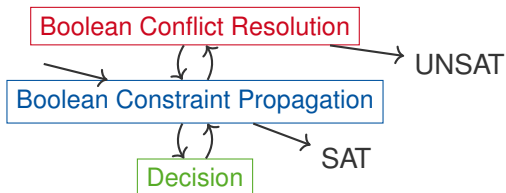
On Variable Orderings in MCSAT for Non-linear Real Arithmetic

SC² 2019

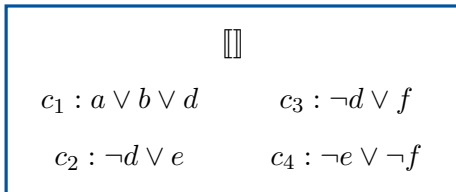
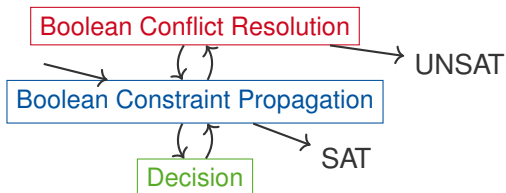
Jasper Nalbach Gereon Kremer Erika Ábrahám

July 10, 2019

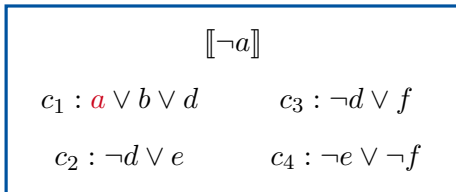
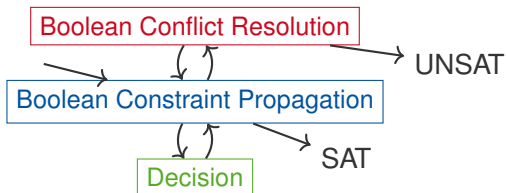
Our MCSAT Approach



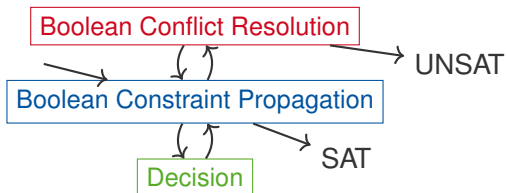
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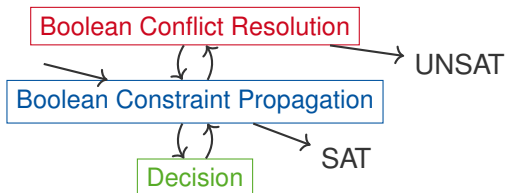
Our MCSAT Approach



Our MCSAT Approach


$$[[\neg a, \neg b]]$$
$$c_1 : a \vee b \vee d$$
$$c_3 : \neg d \vee f$$
$$c_2 : \neg d \vee e$$
$$c_4 : \neg e \vee \neg f$$

Our MCSAT Approach



$$\llbracket \neg a, \neg b, c_1 \rightarrow d \rrbracket$$

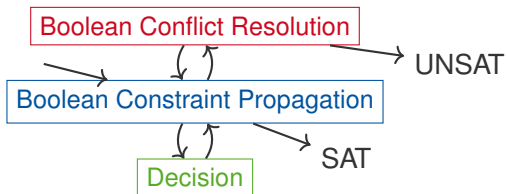
$$c_1 : a \vee b \vee d$$

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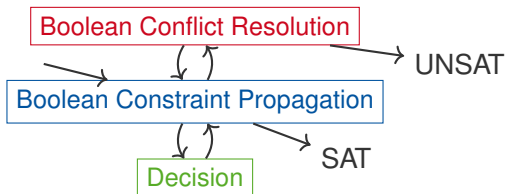
$$c_2 : \neg d \vee e$$

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Our MCSAT Approach


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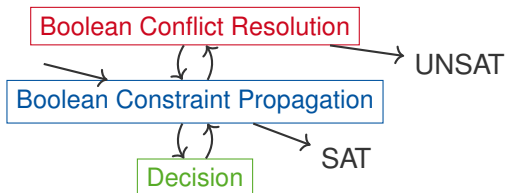


||

$$c_1 : x^2 y > 0 \vee a$$

$$c_2 : x > 0 \vee z = 0$$

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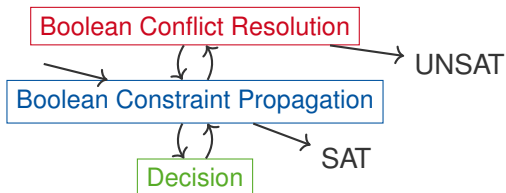


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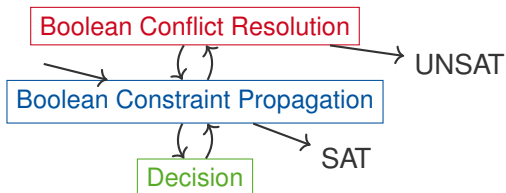


$$\llbracket x^2 y > 0, x \mapsto -1 \rrbracket$$

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Our MCSAT Approach

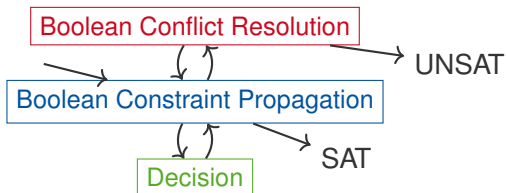


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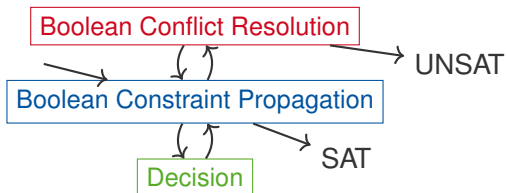


$$\llbracket x^2y > 0, x \mapsto -1, z = 0 \rrbracket$$

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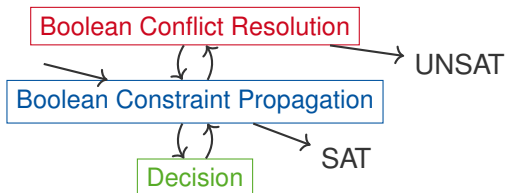


$$\llbracket x^2y > 0, x \mapsto -1, z = 0, y \mapsto (0, \infty) \rrbracket$$

$$c_1 : x^2y > 0 \vee a$$

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Our MCSAT Approach

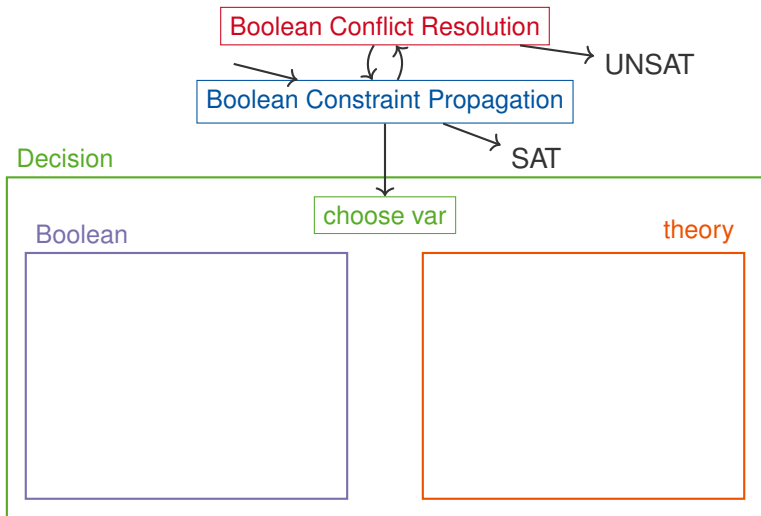


$$\llbracket x^2y > 0, x \mapsto -1, z = 0, y \mapsto 1 \rrbracket$$

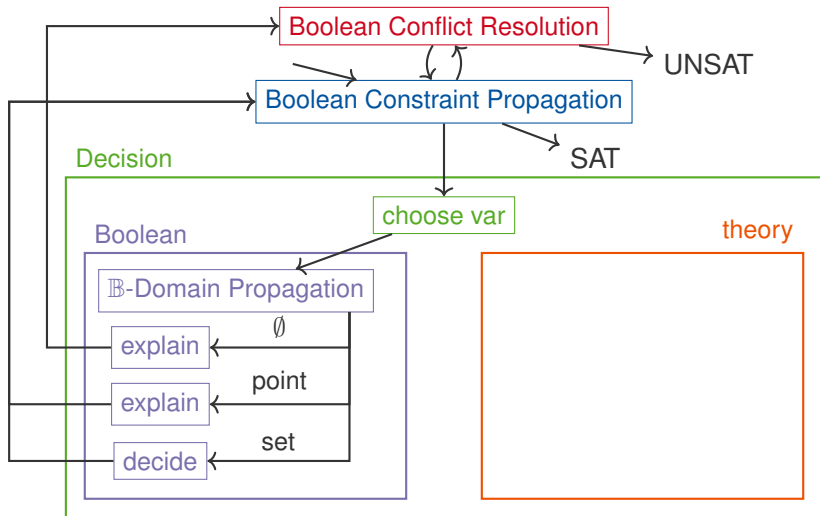
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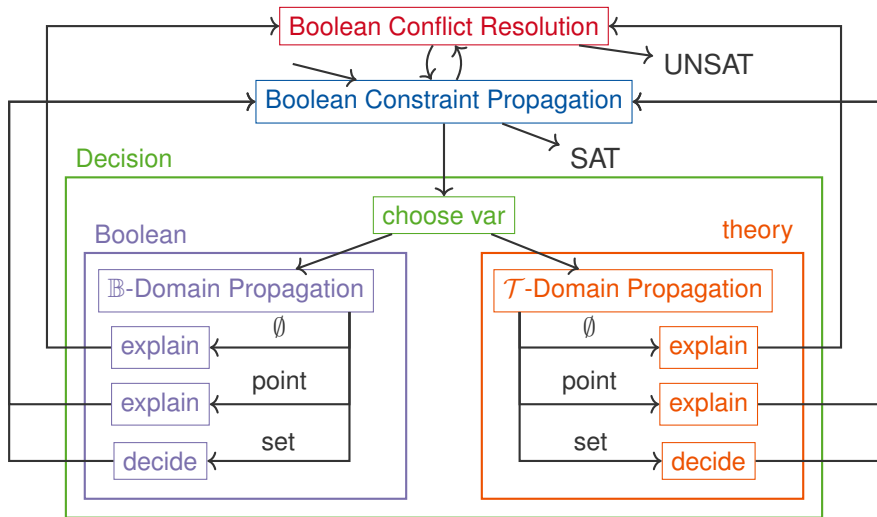
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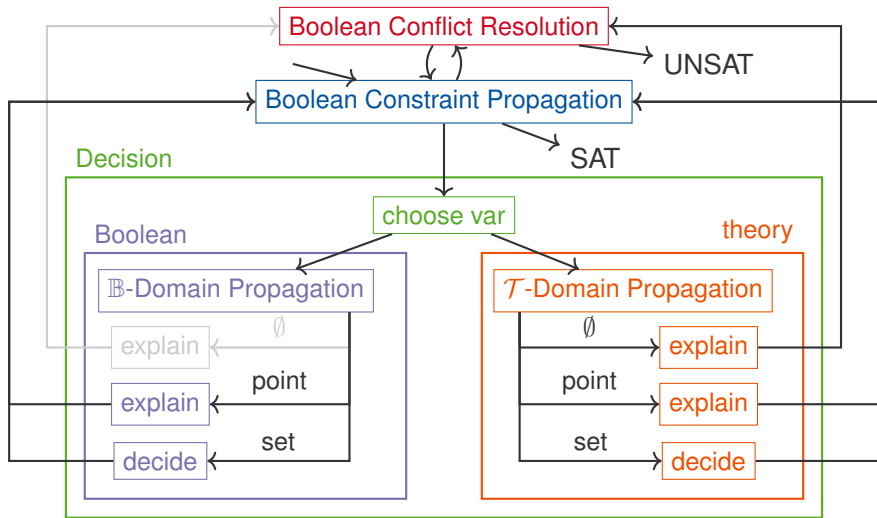
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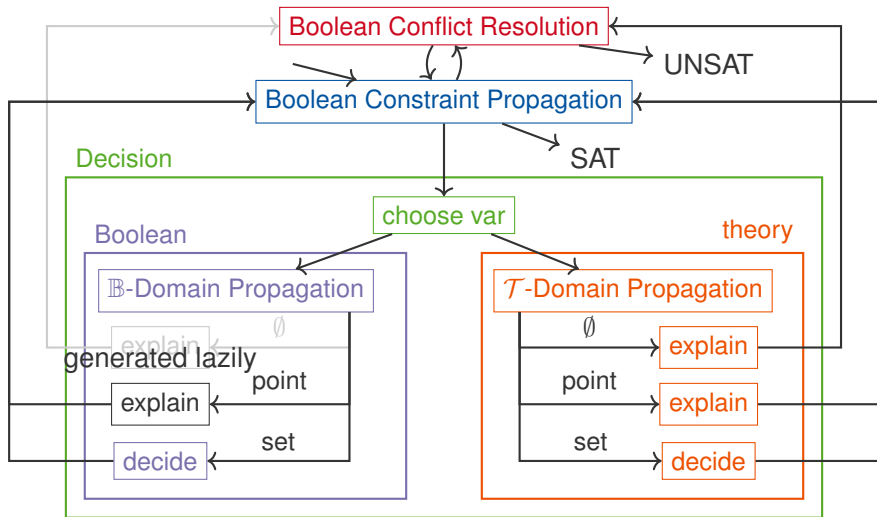
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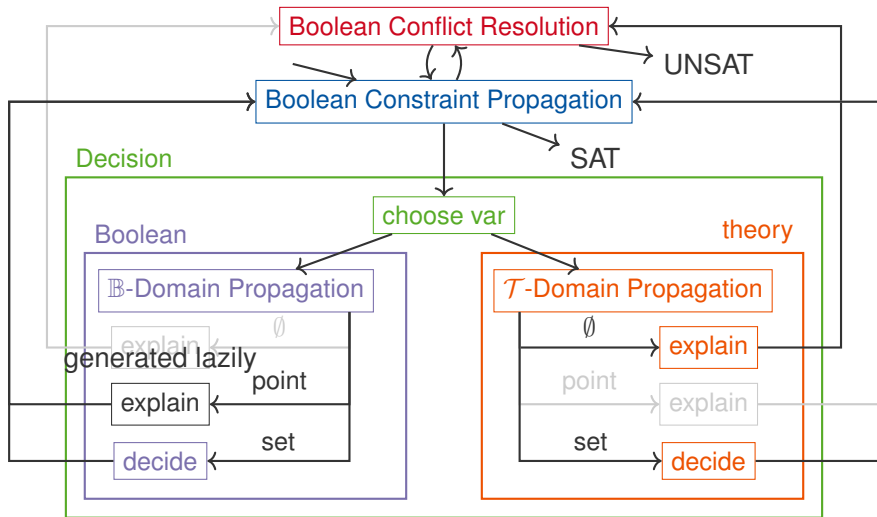
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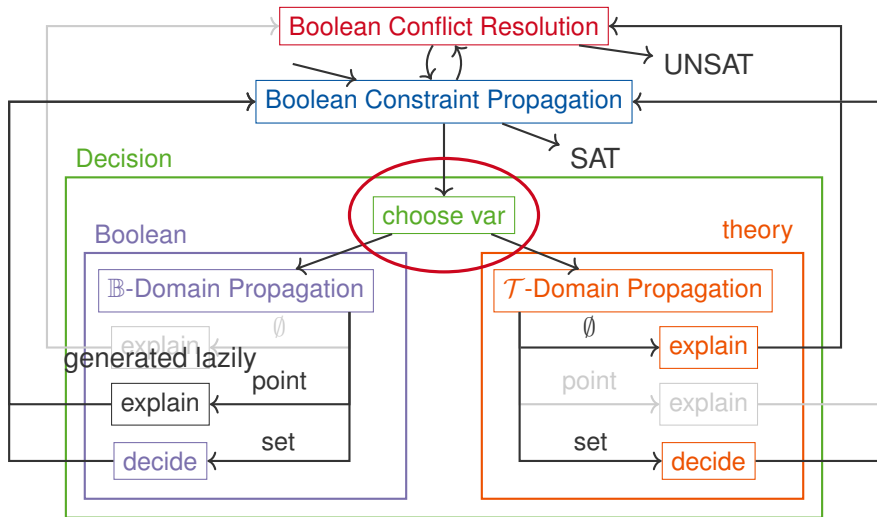
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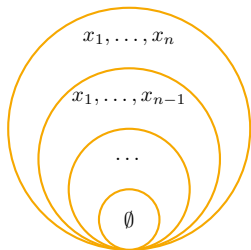
NLSAT's strategy [Jovanović, De Moura 2012]

- ▶ static ordering of theory variables
- ▶ Boolean decisions: literal of a not-yet satisfied clause that is univariate in next theory variable
- ▶ theory decisions: only if no Boolean decision possible

Static vs dynamic orderings

Static orderings

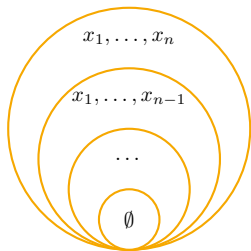
- ▶ induce partial ordering on constraints/clauses



Static vs dynamic orderings

Static orderings

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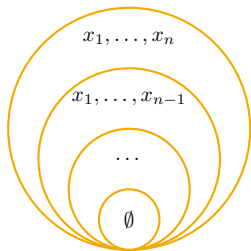


But: How to guess a good ordering in advance?

Static vs dynamic orderings

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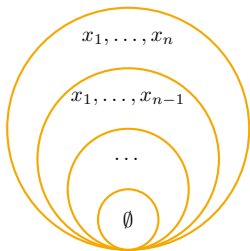
Dynamic orderings

- ▶ assign any undecided theory variable
- ▶ SAT-like heuristics for theory

Static vs dynamic orderings

Static orderings

- ▶ induce partial ordering on constraints/clauses



But: How to guess a good ordering in advance?

Dynamic orderings

- ▶ assign any undecided theory variable
- ▶ SAT-like heuristics for theory

However: not straight-forward!

Extended Polynomial Constraints

CAD explanation backend generates

$$y \sim \text{root}_i(p(z; x_1, x_2, \dots, x_{n-1}, x_n))$$

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Semantics: $\text{root}_i(p(z; x_1, \dots, x_n)) \hat{=} i\text{th root of } z \text{ in } p(z; x_1, \dots, x_n)$

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Assume variable ordering $x_1 < \dots < x_n < y$

[[]]

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$$y \sim \text{root}_i(p(z; x_1, x_2, \dots, x_{n-1}, x_n))$$

Constraint on y

Assume variable ordering $x_1 < \dots < x_n < y$

$$\llbracket x_1 \mapsto \alpha_1, x_2 \mapsto \alpha_2, x_{n-1} \mapsto \alpha_{n-1}, x_n \mapsto \alpha_n \rrbracket$$

Extended Polynomial Constraints

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Change variable ordering $x_1 < \dots < x_{n-1} < y < x_n$

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Extended Polynomial Constraints

CAD explanation backend generates

$$y \sim \text{root}_i(p(z; x_1, x_2, \dots, x_{n-1}, x_n))$$

Constraint on x_n

Change variable ordering $x_1 < \dots < x_{n-1} < y < x_n$

$$\llbracket x_1 \mapsto \alpha_1, x_2 \mapsto \alpha_2, x_{n-1} \mapsto \alpha_{n-1}, y \mapsto \alpha_y, x_n \mapsto \frac{1}{2} \rrbracket$$

Handling incompatible constraints

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$$\llbracket y \sim \text{root}_i(p(z, x_1, x_2, x_3)), x_1 \mapsto a_1, y \mapsto a_y \rrbracket$$

Constraint is temporarily disabled.

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Conflict reoccurs **once** per variable ordering!

Handling incompatible constraints

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$$\llbracket y \sim \text{root}_i(p(z, x_1, x_2, x_3)), x_1 \mapsto a_1 \rrbracket$$

Constraint can safely be re-enabled!

Completeness of MCSAT

Definition (Finite Basis Property)

All literals occurring in the solving process stem from a **finite set** depending on the **input formula** and the **explanation backend**.

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- ▶ The completeness proof of MCSAT relies on the finite basis property!

Finite Basis for Quantifier Elimination Procedures

Assume $x_1 < x_2 < \dots < x_n$

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Observe: Conflict consists of

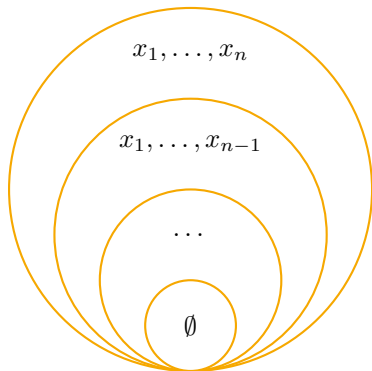
- ▶ assigned variables x_1, \dots, x_{k-1}
- ▶ conflicting variable x_k
- ▶ constraints in x_1, \dots, x_k

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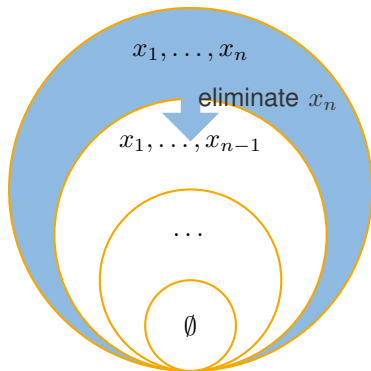


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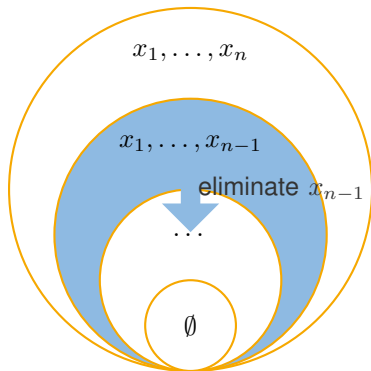


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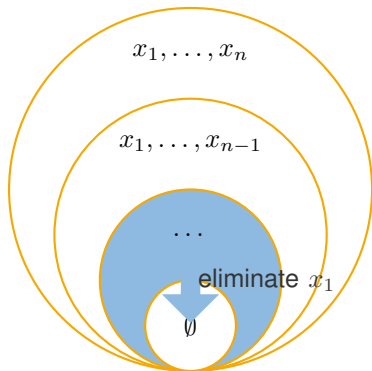


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Finite Basis vs Dynamic Theory Ordering

$$x_1 = 2x_2$$

$$x_2 = 2x_1$$

$$x_1 = 2$$

Finite Basis vs Dynamic Theory Ordering

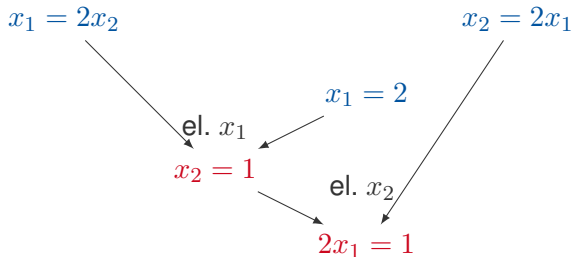
$$x_1 = 2x_2$$

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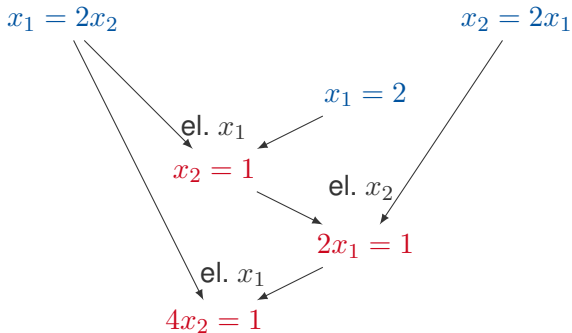
el. x_1

$$x_2 = 1$$

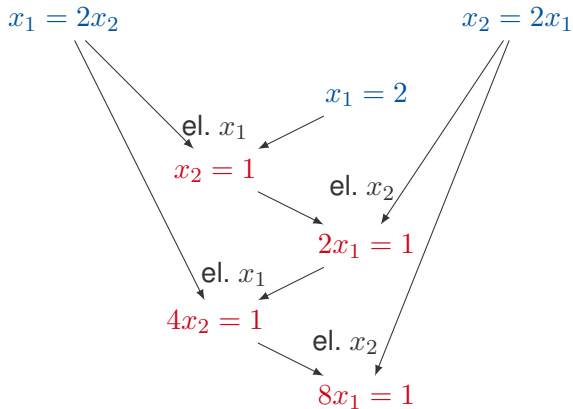
Finite Basis vs Dynamic Theory Ordering



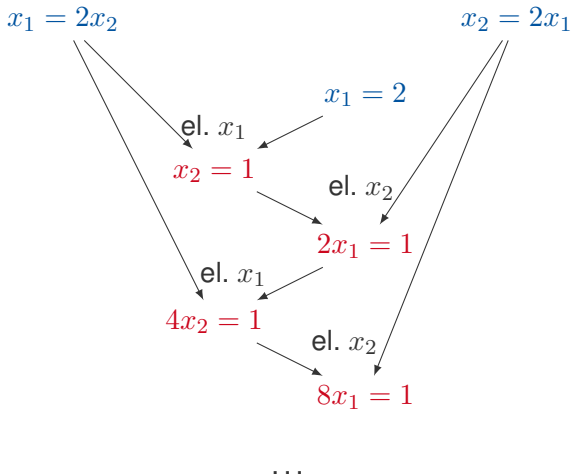
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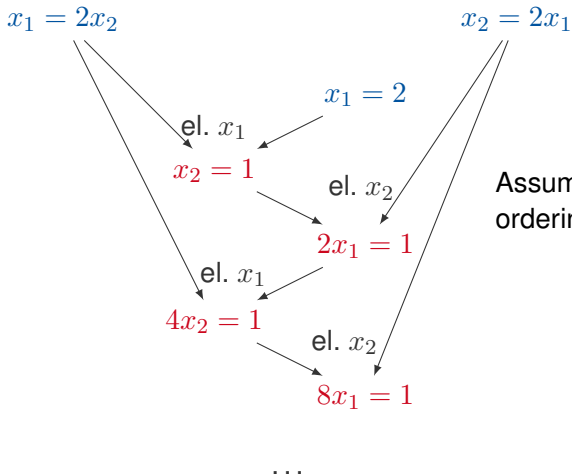
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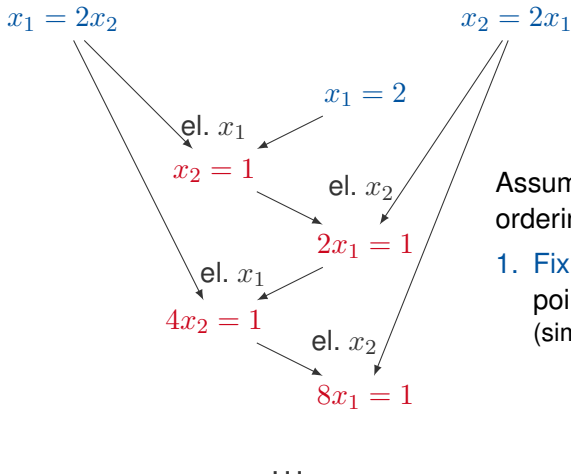


Finite Basis vs Dynamic Theory Ordering



Assume finite basis under fixed ordering. Two solutions:

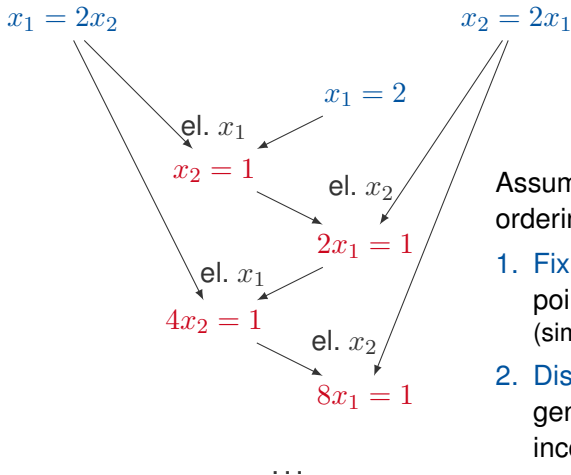
Finite Basis vs Dynamic Theory Ordering



Assume finite basis under fixed ordering. Two solutions:

1. Fix an ordering from some point onwards (similar argument as for restarts)

Finite Basis vs Dynamic Theory Ordering



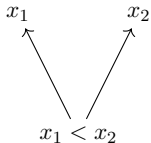
Assume finite basis under fixed ordering. Two solutions:

1. Fix an ordering from some point onwards (similar argument as for restarts)
2. Disable clauses/constraints generated under an incompatible partial ordering

Termination: Compatible Orderings

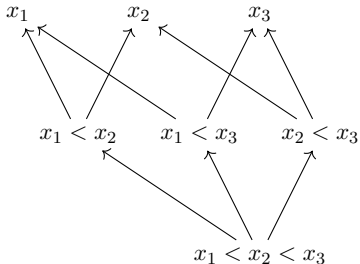
 x_1 $\llbracket x_1 \mapsto ? \rrbracket$

Termination: Compatible Orderings

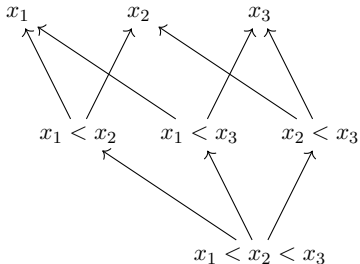


$\llbracket x_1 \mapsto \alpha_1, x_2 \mapsto ? \rrbracket$

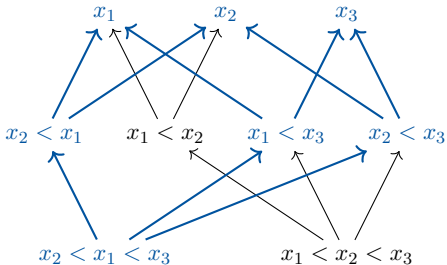
Termination: Compatible Orderings


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Termination: Compatible Orderings

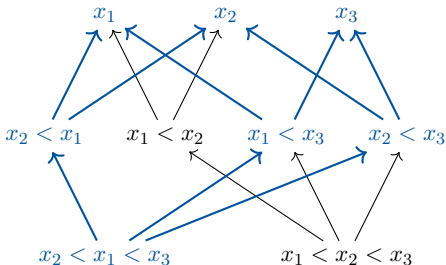

$$\llbracket x_1 \mapsto \alpha_1, x_2 \mapsto \alpha_2, x_3 \mapsto ? \rrbracket$$

Termination: Compatible Orderings



$$\llbracket x_2 \mapsto \alpha_2, x_1 \mapsto \alpha_1, x_3 \mapsto ? \rrbracket$$

Termination: Compatible Orderings



$\llbracket x_2 \mapsto \alpha_2, x_1 \mapsto \alpha_1, x_3 \mapsto ? \rrbracket$

Our intuition: Dynamic orderings let us find a good ordering, but progress is not made by changing the ordering itself!

Experiments: Heuristics

$\mathcal{B}^{dynamic} \mathcal{T}^{static}$

first all Boolean ([activities](#)), then theory ([static](#))

Experiments: Heuristics

 $\mathbb{B}^{dynamic} \mathcal{T}^{static}$ first all Boolean (**activities**), then theory (**static**) $\mathcal{T}^{static} \mathbb{B}^{dynamic}$ first all theory (**static**), then Boolean (**activities**)

Experiments: Heuristics

 $\mathbb{B}^{\text{dynamic}} \mathcal{T}^{\text{static}}$ first all Boolean (**activities**), then theory (**static**) $\mathcal{T}^{\text{static}} \mathbb{B}^{\text{dynamic}}$ first all theory (**static**), then Boolean (**activities**) $\mathbb{B}_{\text{univariate}}^{\text{dynamic}} \mathcal{T}^{\text{static}}$ univariate constraints w.r.t. next theory var, then next theory variable (**static**)

Experiments: Heuristics

 $\mathbb{B}^{dynamic} \mathcal{T}^{static}$ first all Boolean (**activities**), then theory (**static**) $\mathcal{T}^{static} \mathbb{B}^{dynamic}$ first all theory (**static**), then Boolean (**activities**) $\mathbb{B}_{univariate}^{dynamic} \mathcal{T}^{static}$ univariate constraints w.r.t. next theory var, then next theory variable (**static**) $\mathbb{B}_{active}^{dynamic} \mathcal{T}^{static}$ univariate constraints occurring in **not-yet-satisfied clauses**, then next theory variable (**static**)most similar to **NLSAT** strategy

Experiments: Heuristic

$(\mathbb{B} \cup \mathcal{T})^{dynamic}$

Boolean and theory variables treat **equally**, ordered by **activities**

applied for LRA [Jovanovic, Barrett, De Moura 2013].

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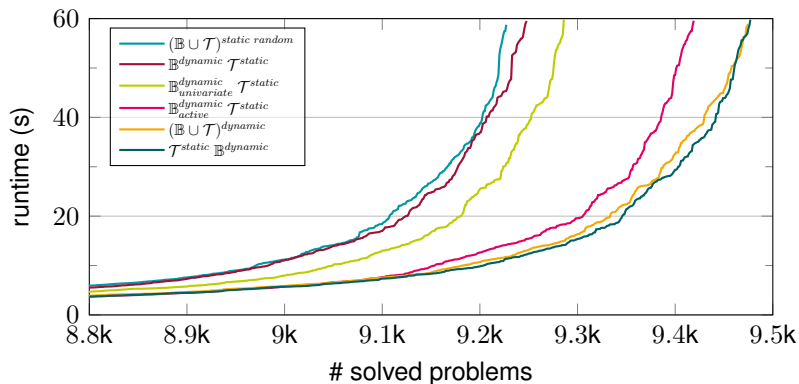
applied for LRA [Jovanovic, Barrett, De Moura 2013].

$(\mathbb{B} \cup \mathcal{T})^{static\ random}$

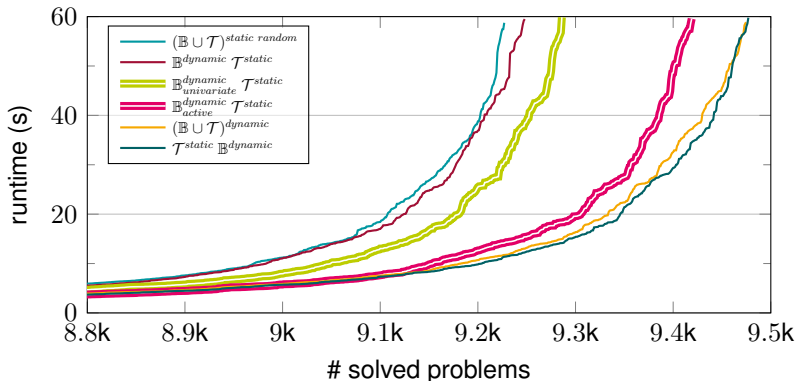
random ordering on all variables is **fixed at beginning**

for reference

Experiments: Results on SMTLIB benchmarks

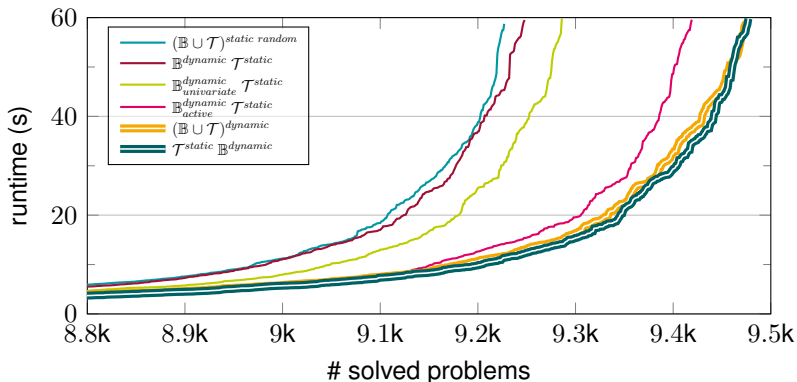


Experiments: Results on SMTLIB benchmarks



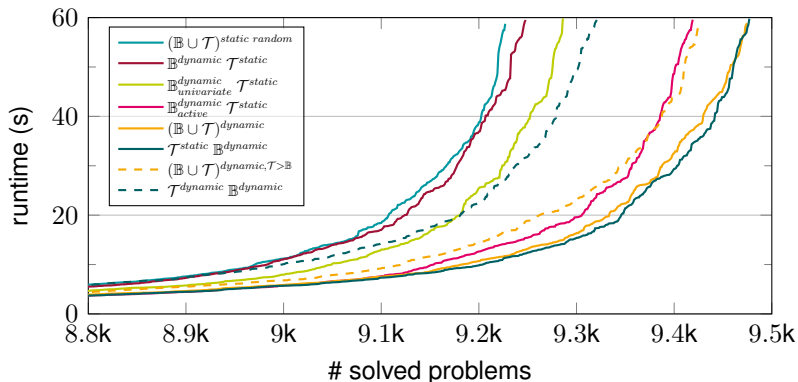
- $\mathbb{B}^{dynamic\ univariate} \mathcal{T}^{static}$ and $\mathbb{B}^{dynamic\ active} \mathcal{T}^{static}$ delay Boolean decisions, avoid unnecessary conflicts, **interlave** model construction

Experiments: Results on SMTLIB benchmarks



- ▶ $\mathcal{T}^{static} \mathbb{B}^{dynamic}$: almost no interleaving of model construction!
- ▶ Does $(\mathbb{B} \cup \mathcal{T})^{dynamic}$ converge towards $\mathcal{T}^{static} \mathbb{B}^{dynamic}$?

Experiments: Results on SMTLIB benchmarks



- ▶ $(\mathbb{B} \cup \mathcal{T})^{dynamic, \mathcal{T} > \mathbb{B}}$: favor theory in case of equal activities
- ▶ $\mathcal{T}^{dynamic} \mathbb{B}^{dynamic}$: theory ordering is activity-based

Further Considerations

- ▶ domain propagation

Simplex on linear parts and complete method

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Simplex on linear parts and complete method

- ▶ explanation backend

Fourier-Motzkin, Virtual Substitution and (One Cell -) CAD

Open Questions

We saw

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- ▶ How do we **prevent overfitting**?
- ▶ Are there **general strategies**?
- ▶ Do we have to **specialize** to certain problem classes?