universität innsbruck

mædmax at School

Learning Selection in Equational Reasoning

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University of Innsbruck

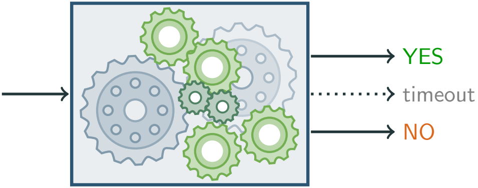
4th Conference on Artificial Intelligence and Theorem Proving

10 April 2019

Equational Theorem Proving

$$0 + x \approx x$$
$$(-x) + x \approx 0$$
$$x + (y + z) \approx (x + y) + z$$
$$x + y \approx y + x$$
$$x \cdot (y \cdot z) \approx (x \cdot y) \cdot z$$
$$(x + y) \cdot z \approx (x \cdot z) + (y \cdot z)$$

$$\mathsf{a} \cdot 0 \approx 0$$



- input: set of equations $\mathcal{E}_0$ and goal $s \approx t$
- output: YES if $\mathcal{E}_0 \vDash s \approx t$ or NO otherwise

Equational Theorem Proving

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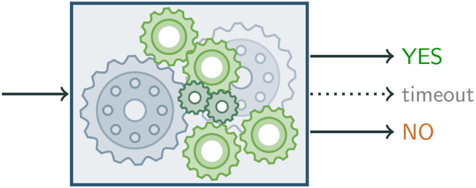

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maedmax

equational theorem proving tool based on maximal ordered completion

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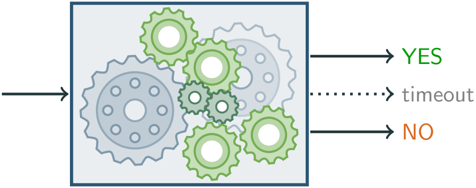

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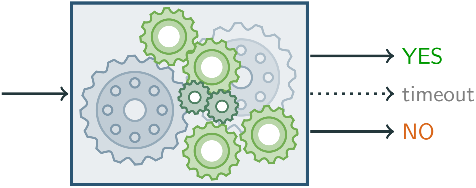

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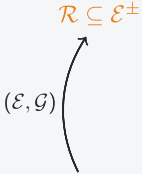
S. Winkler and G. Moser.
Maedmax: A Maximal Ordered Completion Tool.
In *Proc. 9th IJCAR*, LNCS 10900, pp. 472-480, 2018.

Content

Maximal Ordered Completion

0 initialize equations and goals $(\mathcal{E}, \mathcal{G})$ to $(\mathcal{E}_0,\ \{s \approx t\})$

Maximal Ordered Completion



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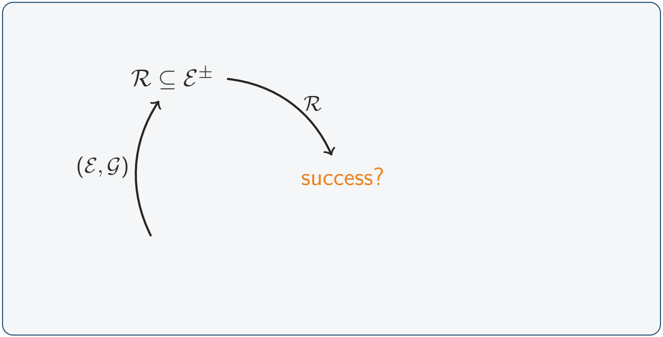

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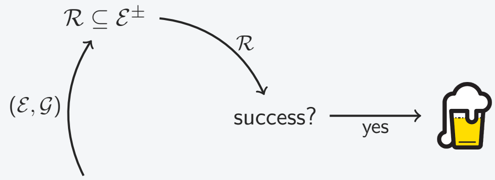

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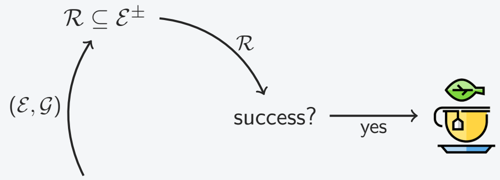

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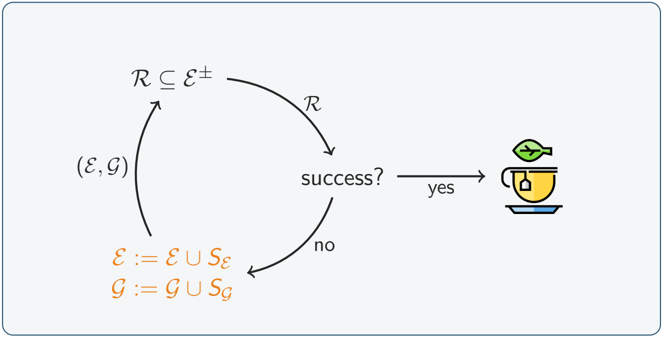

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3 add some critical pairs $S_{\mathcal{E}} \subseteq \mathrm{CP}_{>}(\mathcal{R} \cup \mathcal{E})$ and $S_{\mathcal{G}} \subseteq \mathrm{CP}_{>}(\mathcal{R} \cup \mathcal{E}, \mathcal{G})$

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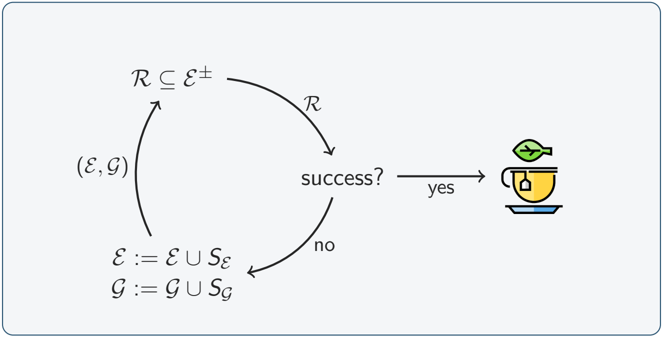

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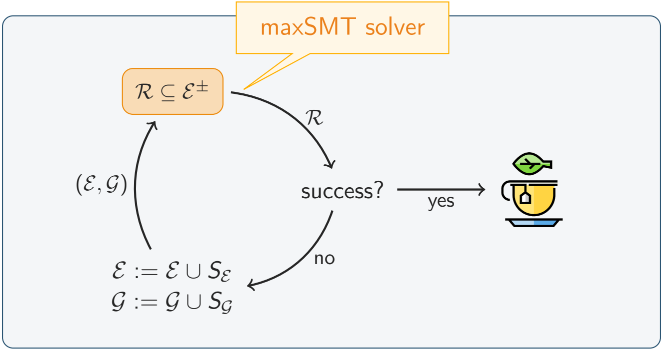

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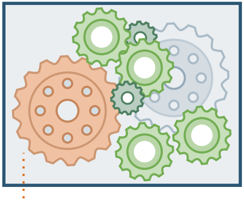
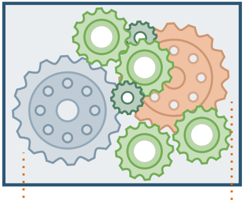
Critical Choice Points



finding $\mathcal{R}$

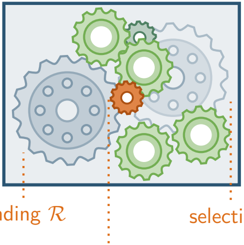
Critical Choice Points



Selecting things

- selection of $S_{\mathcal{E}}$ and $S_{\mathcal{G}}$ is highly critical
- on average only 15% of selected equations and goals used for proof
- learn better choice criteria

Critical Choice Points



Estimating proof progress

- heuristic proof progress estimate: if stuck
  - add additional (old) equations
  - or ultimately restart
- learn better estimate

it's all about the next (small) thing

Content

Learning Equation Selection

Features

- state: number of iterations, equations, and goals
- equation:
  - hand-crafted: polarity, size, size difference, age, orientability, linearity, duplicatingness, # of matches and critical pairs on $\mathcal{E}$

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  - term structure: $\sim$200 *pq*-gram counts

N. Augsten, M. Böhlen, and J. Gamper.
The *pq*-gram distance between ordered labeled trees.
ACM Transactions on Database Systems, 35(1):1–36, 2010.

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Example (*pq*-Grams)

$\mathsf{f}(\mathsf{i}(\mathsf{f}(\mathsf{i}(x), y)), \mathsf{i}(x)) \approx \mathsf{i}(y)$

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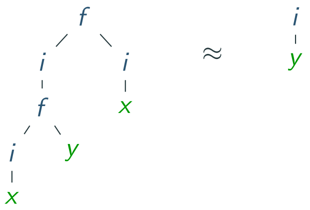

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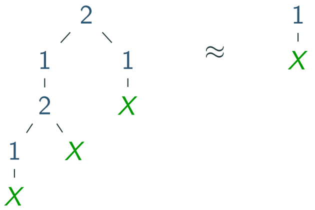

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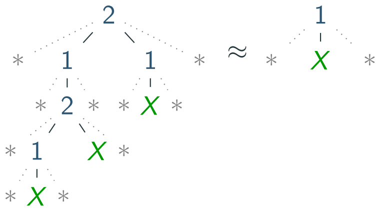

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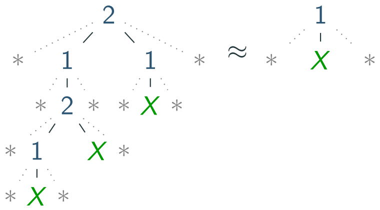

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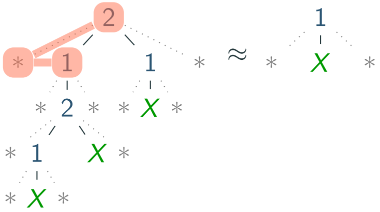

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  2.*.1

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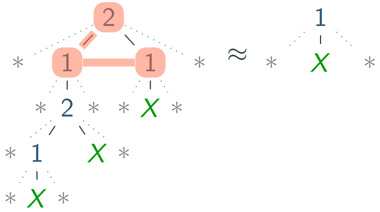

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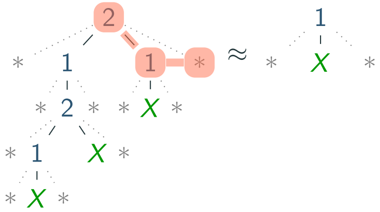

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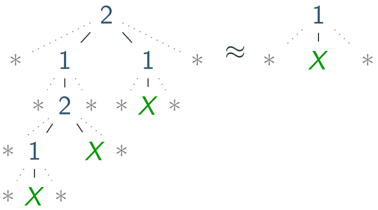

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  2.*.1, 2.1.X, 2.X.*, 1.*.X, 1.X.*,
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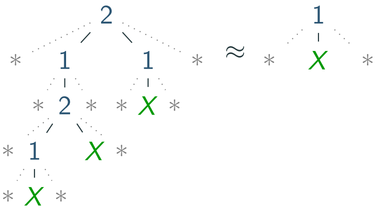

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  1.*.X, 1.X.* and 1.*.X, 1.X.*
- count up to arity 3

Learning Equation Selection

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- state: number of iterations, equations, and go
- equation:
  - hand-crafted: polarity, size, size differen
    linearity, duplicatingness, # of matches
  - term structure: ∼200 *pq*-gram counts

1	polarity	0
2	size	10
3	size diff	6
4	age	42
	⋮	
16	2.2.1	0
17	2.*.1	2
18	2.1.1	1
19	2.1.0	0
20	1.*.X	2
21	1.X.*	2
	⋮	
121	2.2.1	0
122	2.*.1	0
123	2.1.1	0
124	2.1.0	0
125	1.*.X	1
126	1.X.*	1
	⋮	

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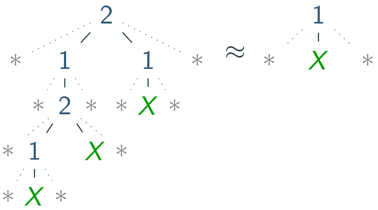

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- *pq*-grams: ht"
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Binary classification

classify equation as positive (useful) if occurs in proof, negative otherwise

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Data collection

- run mædmax in different strategies, recording selections
- check classification of all selected literals upon successful proof
- only 15% positives: duplicate positives for balancing

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Setup

- evaluate data with Python Scikit
- export random forest to json, load into mædmax (OCaml)

Reinforcement loop experiment

- start with random selection $\mathcal{M}_0$

Results

	solved	useful
$\mathcal{M}_0$	206	8%

- run on 897 UEQ problems in TPTP, 60s timeout

Reinforcement loop experiment

- start with random selection $\mathcal{M}_0$
- collect selections $\mathcal{S}_0$ running $\mathcal{M}_0$ with 3 different strategies

Results

	solved	useful	$\lvert\mathcal{S}_i\rvert$
$\mathcal{M}_0$	206	8%	$114K$

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Reinforcement loop experiment

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- build classifier

Results

	solved	useful	$\lvert\mathcal{S}_i\rvert$	precision	recall	f1
$\mathcal{M}_0$	206	8%	$114K$	0.86	0.94	0.9

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Reinforcement loop experiment

- start with random selection $\mathcal{M}_0$
- collect selections $\mathcal{S}_0$ running $\mathcal{M}_0$ with 3 different strategies
- build classifier: $\mathcal{M}_1$ selects literals e with $P_{\text{positive}}(e) > 0.4$

Results

	solved	useful	$\lvert\mathcal{S}_i\rvert$	precision	recall	f1
$\mathcal{M}_0$	206	8%	$114K$	0.86	0.94	0.9
$\mathcal{M}_1$	409	14%				

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Reinforcement loop experiment

- start with random selection $\mathcal{M}_0$
- collect selections $\mathcal{S}_0$ running $\mathcal{M}_0$ with 3 different strategies
- build classifier: $\mathcal{M}_1$ selects literals e with $P_{\text{positive}}(e) > 0.4$
- selections $\mathcal{S}_1$: run $\mathcal{M}_1$ with 3 different strategies, add to $\mathcal{S}_0$

Results

	solved	useful	$\lvert\mathcal{S}_i\rvert$	precision	recall	f1
$\mathcal{M}_0$	206	8%	$114K$	0.86	0.94	0.9
$\mathcal{M}_1$	409	14%	$358K$			

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$\mathcal{M}_0$	206	8%	$114K$	0.86	0.94	0.9
$\mathcal{M}_1$	409	14%	$358K$	0.77	0.83	0.8
$\mathcal{M}_2$	423	15%	$528K$	0.76	0.83	0.79
$\mathcal{M}_3$	433	14%	$704K$	0.78	0.8	0.79

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- ...

Results

time spent on selection rises from 0% (random) to 8-10%

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- run on 897 UEQ problems in TPTP, 60s timeout

Reinforcement loop experiment

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combination with old strategy solves 625

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- feature importance: 60% *pq*-grams, 40% hand crafted
  most useful: literal size, # active literals, # matches and CPs

Learning Proof Progress

State features

- size of $\mathcal{E}$
- memory used
- \# SMT checks
- \# CPs with $\mathcal{R}$
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- get data of about 20K iterations

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Overall gain

+4.5% solved problems combining new selection classifier with old selection, and adding new progress estimate

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- a bit more 

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What's next

- more data
- more/other features
  - more state features?
  - longer *pq*-grams, or vertical ENIGMA features?
- more experiments
  - how to combine with previous selection strategy?
  - use proof progress estimate also for restarts?
- ...