Robust Strategy Schedule Optimization for an Automatic Theorem Prover

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ATPs and Strategies

State-of-the-art automatic theorem provers for FOL:

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DEMO: `./vampire Problems/PUZ/PUZ039-1.p`

CASC 2022 Competition Result Summary (partial)

Typed First-order Theorems +*-/	SnakeFor 1.0	cvc5 1.0	*Vampire* 4.5	Vampire 4.7	iProver 3.6
Solved/250	218/250	195/250	192/250	187/250	138/250
Solutions	218 87%	195 78%	192 76%	187 74%	137 54%

First-order Theorems	SnakeFor 1.0	Vampire 4.7	*Vampire* 4.6	E 3.0	iProver 3.6
Solved/500	460/500	451/500	448/500	384/500	365/500
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SnakeForV4.7: a strategy discovery and schedule construction tool applied to Vampire 4.7 (and running in demonstration-only mode)

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- greedy weighted cover for the schedule creation phase

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*Illustration by Sibylle Ortner, used with permission.

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Use `tptp4X -trandomize` from the TPTP toolset to:

- randomize the order of commutative logical operations
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Can now be invoked from Vampire (`--shuffle_input on`)
as well as "internal" shuffling (`--random_traversals on`)

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- focus on speeding up the best known solution

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Local search for strategy improvement

- vary one option at a time
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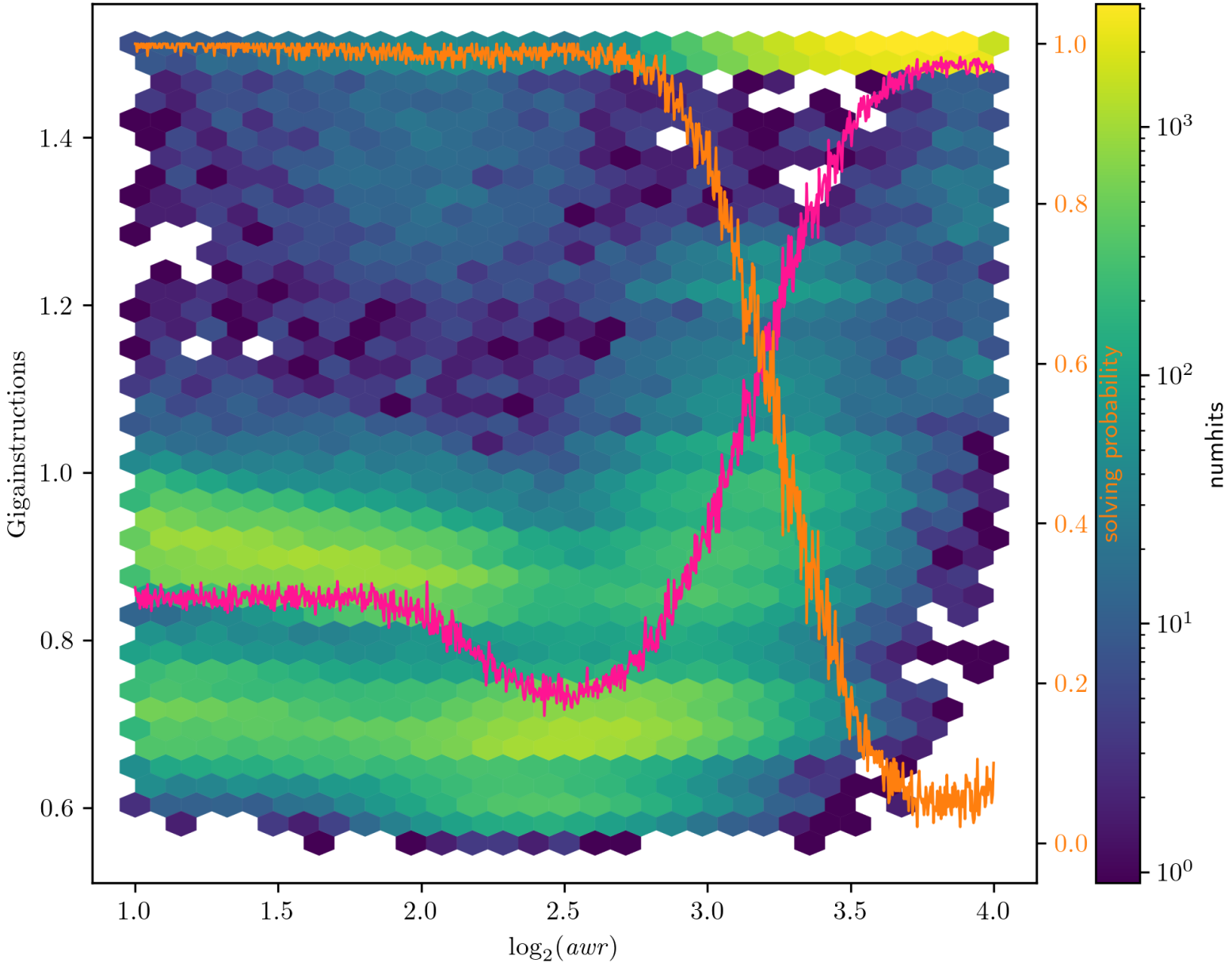
DEMO: `protocol.txt`

DEMO cont.: an AWR Plot



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Greedy Weighted Set Cover

Starting with the empty schedule $\mathcal{S} = \emptyset$
Loop adding to $\mathcal{S}$ an (s, i) maximizing $|S_{(s,i)} \setminus c(\mathcal{S})|/w_{(s,i)}$

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- Collect more data: e.g., (s, i) solves p with probability 0.8
- Assuming strategy independence: if current $\mathcal{S}$ solves p with prob. 0.5, adding (s, i) to $\mathcal{S}$ will improve by $0.8 \cdot 0.5$ to 0.9

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Thank you!

One more experiment with randomness

Clause Selection and Age-weight Ratio

Vampire alternates between selecting the next given clause by age (old first) and by weight (light first) under a given ratio.

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configuration	solved	uniques	additional
base	8725	12	8725
rnd1	8747	8	91
rnd2	8744	16	37
rnd3	8768	23	37
rnd4	8735	14	21
rnd5	8741	16	16

base = `-sa discount -awr 1:1 -t 10`

Related work

Related work ATP:

- MaLeS [Kühlwein&Urban, 2015]
- BliStr → BliStrTune → EmpireTune → Grackle [Urban, Jakubův, . . .]
- HOS-ML [Holden& Korovin, 2021]
- Genetic breeding [Schäfer and Schulz, 2015]

Related work SMT:

- MachSMT [Scott et al., 2021]

Related work algorithm configuration etc:

- [Hoos,Hutter,. . .]