Lightweight Online Learning for Sets of Related Problems in Automated Reasoning






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Motivations

- Automated (logical) reasoning
  - Become mature technology over the past decades
  - Wide applications (e.g., formal verification, theorem proving)
  - Often tackle problems NP-hard and beyond
  - **Scalability** is still a concern

- Machine Learning has been successfully applied in diverse domains
  - Perception
  - Natural language processing
  - …
  - **Automated reasoning?**

ML for AR: status quo

Approach 1: Replace solver as a whole (end-to-end approach)

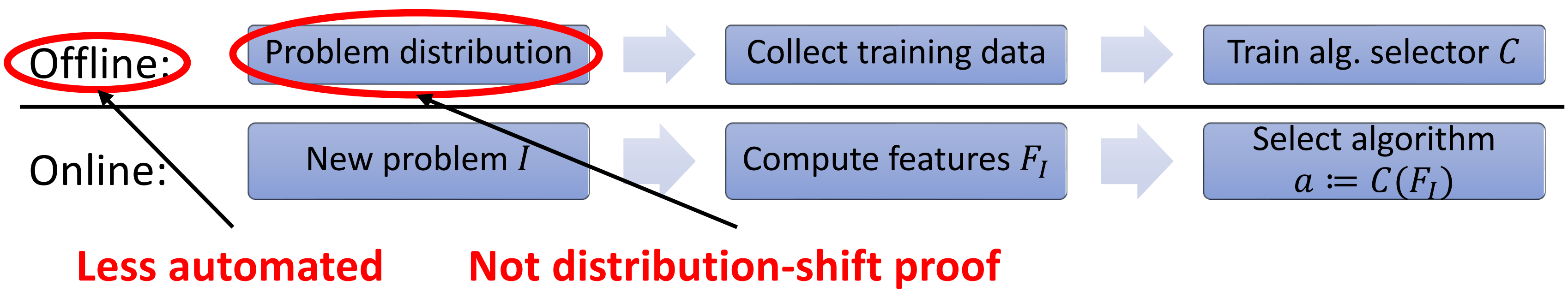
- **Limited scalability**

Approach 2: Replace internal (e.g., branching) heuristics with a ML model

- **Large overhead** compared to hand-crafted heuristics

Approach 3: Meta-algorithmic design

- Currently **most successful**



This work: Self-Driven Strategy Learning (SDSL)

- **Key observation:** many AR tasks involve solving a set $\boldsymbol{S}$ of related problems
  - Bounded Model Checking
  - Iterative abstraction refinement (e.g., CEGAR)
  - Counter-example-guided inductive synthesis (CEGIS)
  - Max-satisfiability
  - …
- Possible to narrow the scope of problem distribution down to this set $\boldsymbol{S}$
- **Key idea: Collect data and learn a model *on-the-fly***

SDSL: a sketch

Given a set of related problems $S \coloneqq \{I_1, I_2, I_3, \dots\}$ and a space of solving strategies $V \coloneqq \{v_0, v_1, v_2, v_3, \dots\}$:

Normal execution:

$\mathbf{Check}(I_1, v_0)$

$\mathbf{Check}(I_2, v_0)$

$\mathbf{Check}(I_3, v_0)$

…

SDSL: a sketch

Given a set of related problems $S \coloneqq \{I_1, I_2, I_3, \dots\}$ and a space of solving strategies $V \coloneqq \{v_0, v_1, v_2, v_3, \dots\}$:

SDSL execution:

$\mathbf{Check}(I_1, v_0)$	$\mathbf{Check}(I_2, v_0)$	$T = \mathbf{fit}(D)$	$\mathbf{Check}(I_3, v_k)$
$\mathbf{Check}(I_1, v_2)$	$\mathbf{Check}(\mathrm{I}_2, v_3)$	$v_k = \arg\min_{v \in V} T(v)$	$\mathbf{Check}(I_4, v_k)$
…	…		…

$I_1, v_0 \to a$	$I_2, v_0 \to e$	$I_3, v_k \to m$
$I_1, v_2 \to b$	$I_2, v_3 \to f$	$I_4, v_k \to n$
…	…	…

Dataset D: $(S, V) \to Cost$

ML model T

Wait, what about the overhead?

Data collection time **amortizes** in many practical applications

SDSL: a calculus view

$$\frac{i < \mathbf{K} \quad \mathbf{check}(f_i, v) = \text{UNSAT}}{i, v \Longrightarrow i+1, v}\ \textbf{(Next)}$$

$$\frac{i = \mathbf{K} \quad \mathbf{check}(f_i, v) = \text{UNSAT}}{i, v \Longrightarrow \text{FAIL}}\ \textbf{(Failure)}$$

$$\frac{\mathbf{check}(f_i, v) = \text{SAT}}{i, v \Longrightarrow \text{SUCCESS}}\ \textbf{(Success)}$$

$$\frac{v_s \in \mathcal{V} \quad j \leq i \quad c = \mathbf{cost}(f_j, v_s)}{i, v, D, T \Longrightarrow i, v, D \cup \{\langle v_s, j, c\rangle\}, T}\ \textbf{(Collect)}$$

$$\frac{T' = \mathbf{fit}(D)}{i, v, D, T \Longrightarrow i, v, D, T'}\ \textbf{(Train)}$$

$$\frac{\mathcal{V}_s \subseteq \mathcal{V} \quad v' = \arg\min_{v_s \in \mathcal{V}_s} T(v_s, i)}{i, v, D, T \Longrightarrow i, v', D, T}\ \textbf{(Strategize)}$$

1) After every **Next**, apply **Collect** *m* times, then apply **Train**
2) Apply **Strategize** whenever i is updated
3) Override 1) when some learning budget is exhausted
4) Terminate whenever **Success** or **Failure** applies

Which strategy to choose? **Which representation?**

SDSL: Collecting informative data

- If $|V|$ is too small, it might not contain good strategy
- If $\mathrm{m} \ll |V|$, how we sample determines the quality of the dataset
  - We need sufficient low-cost strategies in the dataset
  - Explicitly bias towards low-cost strategies with MCMC-sampling (Metropolis-Hastings)

1) Choose a current strategy v
2) Propose to replace v with v', from distribution $\mathrm{q}(v'|v)$
3) If $cost(f, v') \leq cost(f, v)$, accept v' as the current strategy
4) Else, accept v' as the current strategy with probability $\mathrm{a}(v \rightarrow v')$
5) Go to step 2

Case study: Bounded Model Checking

- A widely-used formal verification technique
  - Find bugs
  - Establish formal guarantees

- Check a property P for a transition system over executions bounded by k:

$$bmc(k', k) := I_0 \wedge \bigwedge_{i=0}^{k-1} \rho(i, i+1) \wedge \bigwedge_{i=0}^{k'} P_i \wedge \left(\bigvee_{i=k'+1}^{k} \neg P_i \right)$$

- A Bounded Model Checker solves a set of BMC formulas:

$$\mathcal{F} = \{bmc(k - s, k) \mid k = i \cdot s, 1 \leq i \leq \mathbf{K}\}$$

Step size

BMC Configurations

- **Kissat**: BMC (using Kissat as the underlying SAT solver)

- **Kissat + SDSL**: BMC with self-driven strategy learning
  - Rely on expert knowledge to pick the strategy space

Strategy space I:

Bruno Dutertre, “An Empirical Evaluation of SAT Solvers on Bit-vector Problems”, the SMT workshop, 2020

~~*compacting*:~~	~~compacting internal variables~~
chrono:	support for chronological backtracking
decompose:	elimination of equivalent literals
eagersubsume:	apply subsumption to recently learned clauses
elim:	bounded-variable elimination
elimgates:	recognize clauses that encode and, xor, and if-then-else
~~*lucky*:~~	~~try predefined satisfying assignments~~
probing:	failed-literal probing
rephase:	periodically switch preferred variable polarity
~~*scan-index*:~~	~~optimized watched literal search~~
stabilize:	switch between two heuristic modes
subsumption:	clause subsumption
ternary:	hyper ternary resolution
vivify:	clause vivification
~~*walk*:~~	~~random walks~~

Figure 2: Tested Features in CaDiCaL. Each feature is enabled by default and enables specific CaDiCaL procedures. Except for *scan-index*, all are controlled by command-line options

Strategy space II:

What options might influence kissat's behaviour the most? #25

Closed

arminbiere commented on Jun 16, 2022 Owner ···

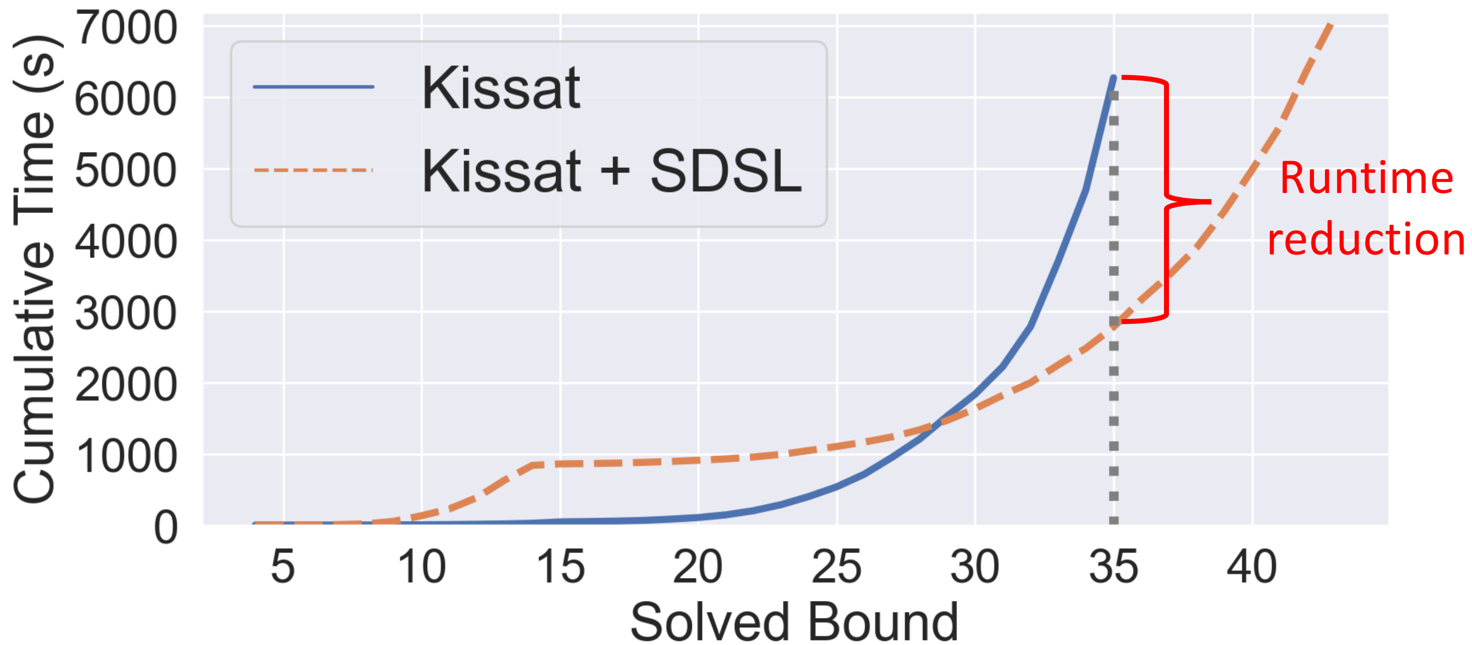
Yes: tier1, chrono, stable, walkinitially, target, phase is a good set. In essence I went over the code and tried to remove actual code and also options. What is left in 'sc2022-light' either had some influence on certain benchmarks or is important for testing and (delta-)debugging (such as all those '--...init=' options). For instance, for hardware miters playing with the '--sweep...' options can give you large benefits (which are problematic for other benchmarks though and not the best you can do for miters anyhow). So this set is pretty close to a robust setting for SAT competition alike benchmarks.

Unrolling the unsolved benchmarks

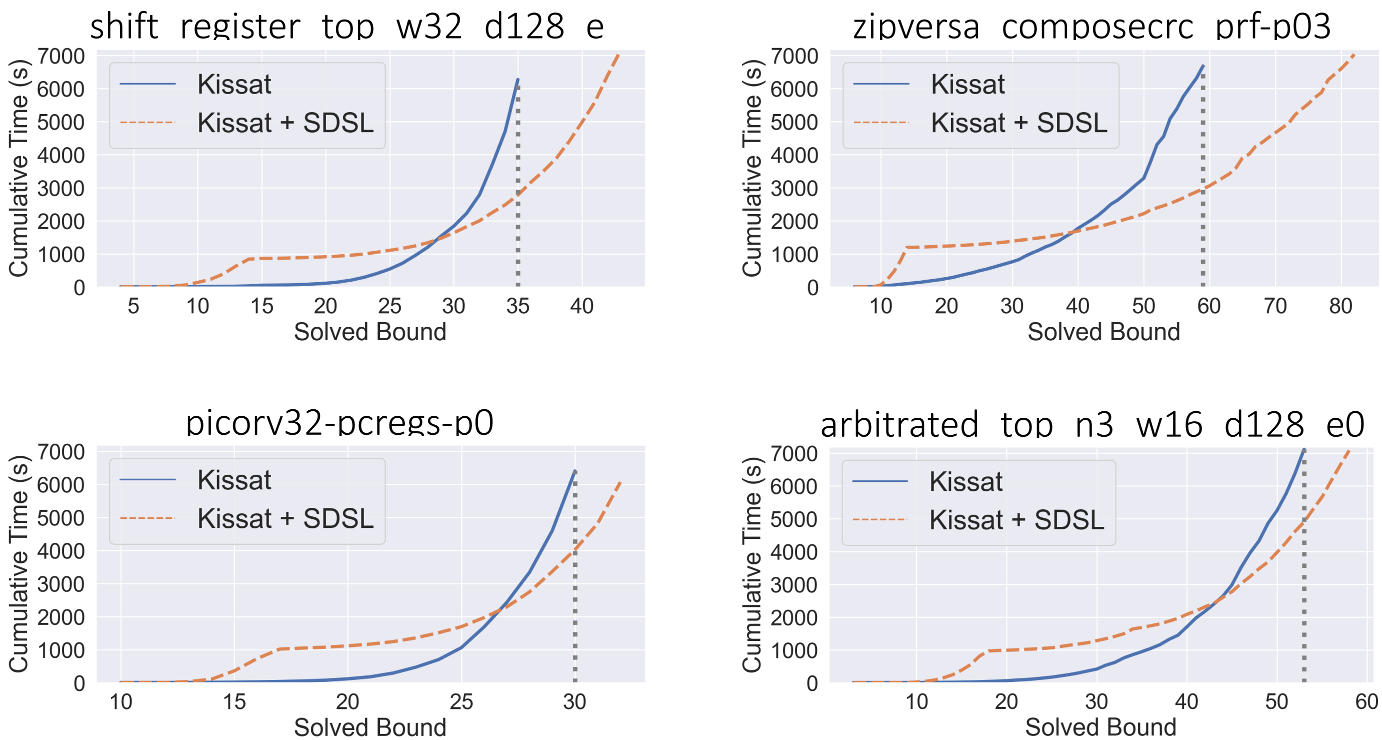
- Unsolved benchmarks from Hardware Model Checking Competition
- Each job is given 2 hours CPU time, one physical core, and 8 GB memory

Unrolling the unsolved benchmarks: example

shift_register_top_w32_d128_e0



Unrolling the unsolved benchmarks: more examples



SDSL certifies larger bounds in > 90% of the cases

Unrolling the unsolved benchmarks

Metrics:

- **Bound**: largest solved bound within 2 hours
- **Time**: time (in seconds) to reach the largest commonly solved bound

	KISSAT + SDSL		KISSAT		PONO
Step size	**Time**	**Bound**	**Time**	**Bound**	**Bound**
1	**4811**	**52.6**	6354	48.7	43.1
10	**2927**	**57.5**	3712	55.4	55.4

Comparison against SoTA Model Checkers

- 89 unknown and satisfiable competition benchmarks
- Additional baselines:
  - **AVR Portfolio**: 16 threads, winner of HWMCC'2020
  - **Pono Portfolio**: 13 threads, winner of HWMCC'2019
- Each thread is given 1 hour CPU time and 8 GB memory

Config.	**Threads**	**Slv.**	**Time**	**Unique**
KISSAT + SDSL	1	**68**	27362	**7**
KISSAT	1	61	6358	0
AVR PORTFOLIO	16	48	12113	2
PONO PORTFOLIO	13	63	10723	0
VIRTUAL BEST	31	72	24700	–

SDSL solves 7 **unsolved** problems during the competition

Summary

- Self-Driven Strategy Learning:
  - A general online Learning methodology potentially applicable to many automated reasoning tasks

- Case study on BMC on hardware designs
  - Consistent improvement over state-of-the-art on satisfiable instances

- **Bigger picture:**
  - **Let ML make high-level decisions, let AR work out the details**

Paper: https://arxiv.org/abs/2305.11087

SCAN ME