A Scalable Two Stage Approach to Computing Optimal Decision Sets

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Problem and state of the art

Problem example

(classication scenario)

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#	Day	Venue	Weather	TV Show	*Date?*
e_1	Weekday	Dinner	Warm	Bad	No
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IF TV Show $=$ Bad $\wedge$ Day $=$ Weekend **THEN** Date $=$ Yes

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unordered set of *if-then* rules

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highly interpretable!

rule-based models

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⬇

"transparent" **and easy to interpret**

rule-based models

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“*transparent*” **and easy to interpret**

⬇

come in handy in XAI

State of the art — a typical approach

input : training data E
output: *smallest*[a] decision set ϕ

```
N ← LB                              # N equals a lower bound on |φ|, which is often set to 1
while True:
    F ← Encode(E, N)                # encode problem "is there a decision set φ of size N for data E?"
    (st, μ) ← Oracle(F)             # call a reasoning oracle to answer the question
    if st is True:
        break
    N ← N + 1
φ ← ExtractRules(μ)                 # extract decision set φ from satisfying assignment μ
return φ
```

[a] wrt. the number of rules or literals

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encoding is too large!

(does not scale)

Our approach

divide the process into two stages:

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each class is computed *independently*

Our take on the problem

divide the process into two stages:

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- MaxSAT-based
- incremental!
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each class is computed *independently*

the idea is to scale better

each rule is a solution to MaxSAT formula

$$\psi \triangleq H \wedge S$$

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H — hard clauses

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   - rule must cover $\geq$ 1 right instances

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$\mathcal{H}$ — hard clauses

1. **coverage constraints:**
   - **rule must cover $\geq$ 1 right instances**
2. **discrimination constraints:**
   - **rule must not cover any wrong instances**

each rule is a solution to MaxSAT formula

$$\psi \triangleq \mathcal{H} \wedge \mathcal{S}$$

$\mathcal{H}$ — hard clauses	$\mathcal{S}$ — soft clauses
1. coverage constraints: • rule must cover ≥ 1 right instances 2. discrimination constraints: • rule must not cover any wrong instances	• minimize the number of used literals

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$\mathcal{H}$ — hard clauses

1. coverage constraints:
   - rule must cover $\geq$ 1 right instances
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$\mathcal{S}$ — soft clauses

- minimize the number of used literals

$\mathcal{O}(K + M)$ variables and $\mathcal{O}(K \times M)$ clauses

(K — number of features, M — number of training instances)

Stage 2 — computing rule cover

#	Day	Venue	Weather	TV Show	*Date?*
e_1	Weekday	Dinner	Warm	Bad	No
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$\pi_1 = [\ \textbf{IF}\ \text{Day} = \text{Weekday} \quad \textbf{THEN}\ \text{Date} = \text{No}\ ]$

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$\pi_1 = [$ **IF** Day $=$ Weekday **THEN** Date $=$ No $]$

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$b_j \in \{0, 1\}$ **and** $s_j = |\pi_j|$ **for each** π_j

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	π_1	π_2	π_3	π_4
a_{ij}	1	1	0	0
	0	0	1	1
s_j	1	1	1	1

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$$\textbf{minimize} \sum_j s_j \cdot b_j$$

$$\textbf{subject to} \sum_j a_{ij} \cdot b_j \geq 1, \forall i$$

Breaking symmetric rules

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for each rule, add one clause enforcing
all following rules to cover $\geq$ 1 other instance

Experimental results

Experimental setup

- **machine configuration:**
  - Intel Xeon Silver-4110 2.10GHz with 64GByte RAM

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  - **3–384 features** (one-hot encoded)
  - **14–67557 training** instances

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- **competition tested:**
  - **mds_2** – minimization of number of rules

[1] `https://github.com/alexeyignatiev/minds`

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  - **ruler$_*^\circ$**
    - **same code base** and SAT solver – Glucose 3

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    - **ruler$_*^\circ$+b** – symmetry breaking *enabled*

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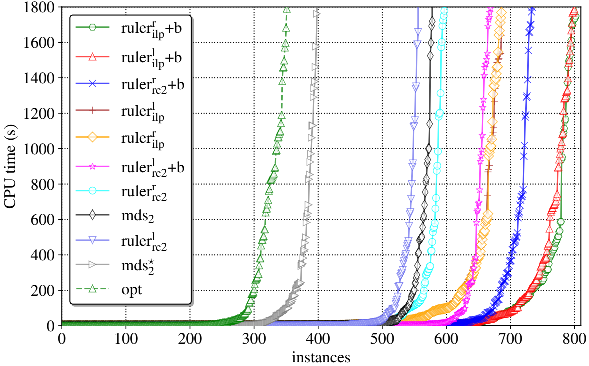
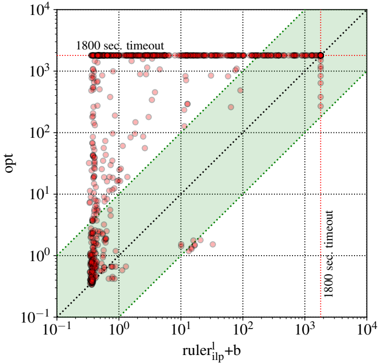
Results – performance comparison



(a) raw performance



(b) ruler$^{l}_{ilp}$+b vs. *opt* detailed

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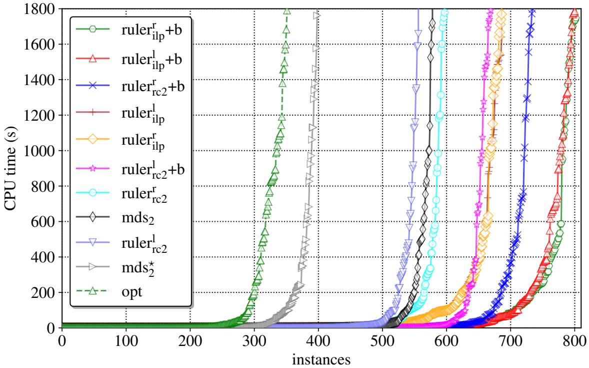

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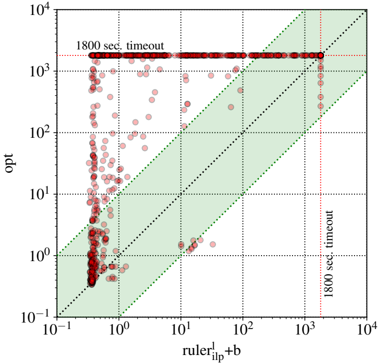

(b) $\text{ruler}^{\text{l}}_{\text{ilp}}$+b vs. *opt* detailed

$\text{ruler}^{\text{l}}_{\text{ilp}}$+b vs. **opt** — **up to 4 orders of magnitude** performance improvement

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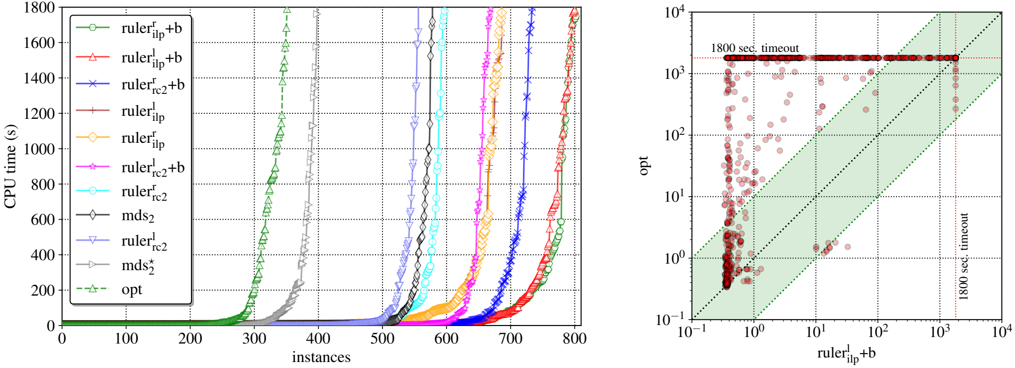

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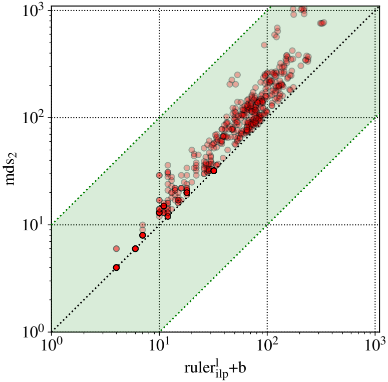
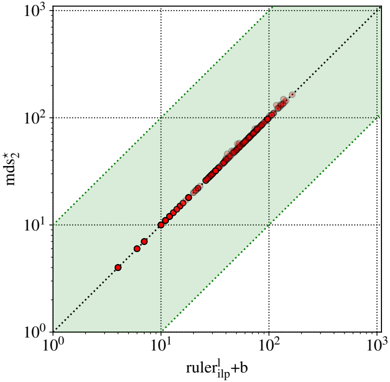
ruler$^{l}_{ilp}$+b vs. **opt** — **up to 4 orders of magnitude** performance improvement

breaking symmetric rules — avg. # of rules goes down **from 19604.4 to 563.7**

Results – model size comparison



(a) literals or rules: $\mathrm{ruler}^{\mathrm{l}}_{\mathrm{ilp}}$+b vs. mds_2



(b) literals or lexicographic: $\mathrm{ruler}^{\mathrm{l}}_{\mathrm{ilp}}$+b vs. $mds^{\star}_2$

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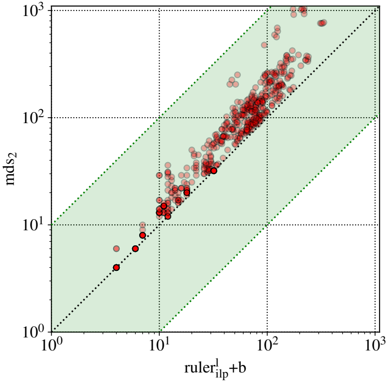

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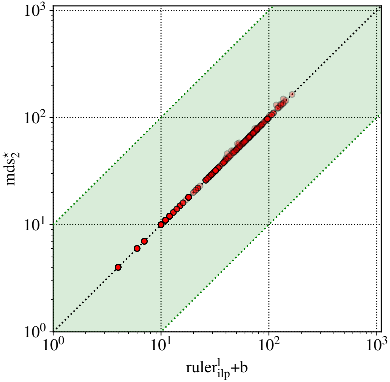

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$\mathbf{ruler}^{\mathbf{l}}_{\mathbf{ilp}}$**+b** vs. $\mathbf{mds_2}$ — halves avg. size (62.2 vs. 116.2)

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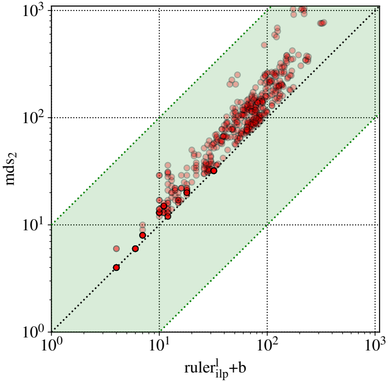

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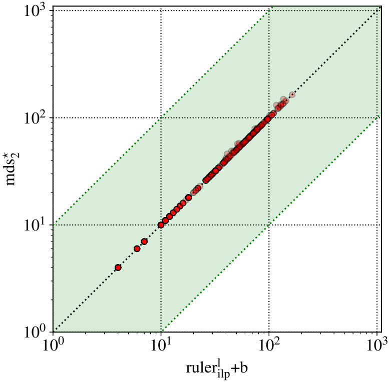

(b) literals or lexicographic: ruler$^{\mathsf{l}}_{\mathsf{ilp}}$+b vs. *mds*$_2^\star$

ruler$^{\mathsf{l}}_{\mathsf{ilp}}$+b vs. **mds$_2$** — halves avg. size (62.2 vs. 116.2)

mds$_2^\star$ vs. **mds$_2$** — *lexicographic optimization* pays off

(but slower!)

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        - decision trees

Questions?