Statistical Comparison of Algorithm Performance Through Instance Selection

T. Matricon, M. Anastacio, N. Fijalkow, L. Simon and H. H. Hoos

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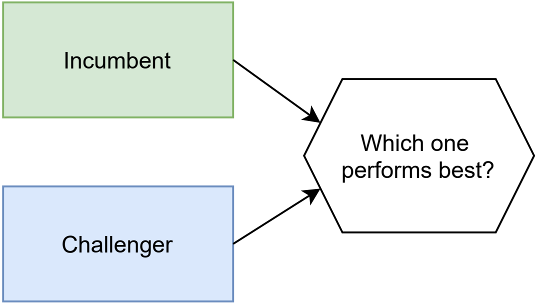
The Problem



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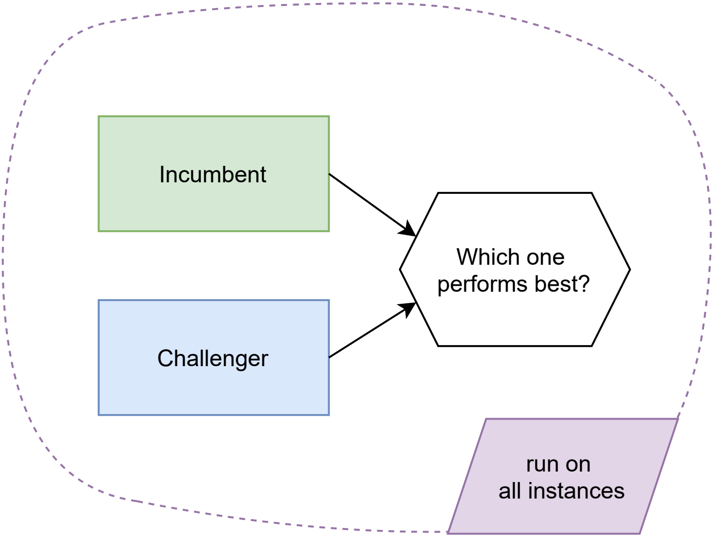
Incumbent
Challenger
Which one performs best?
run on all instances

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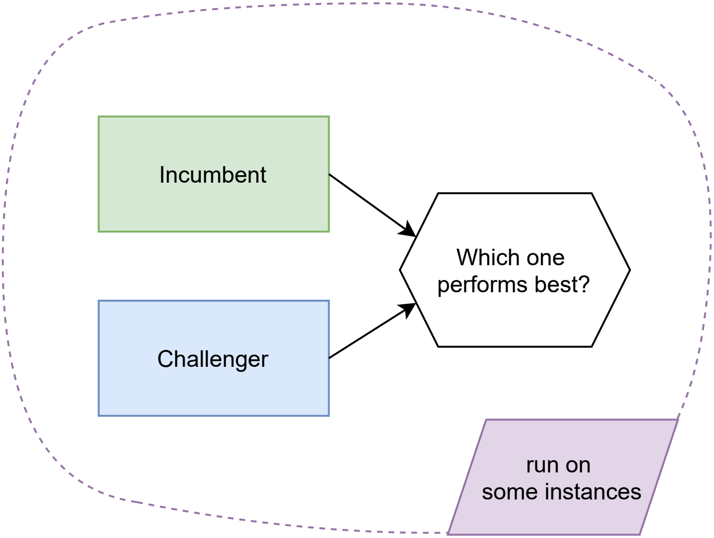
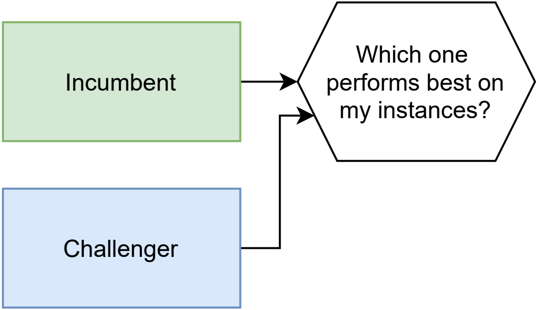

Incumbent
Challenger
Which one performs best?
run on some instances

Per Set Efficient Algorithm Selection (PSEAS) Problem



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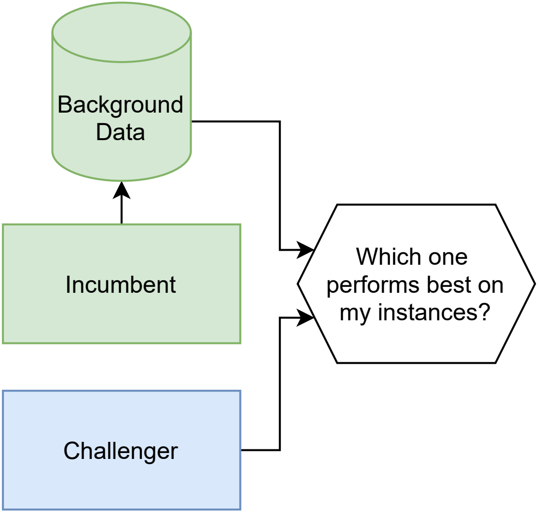

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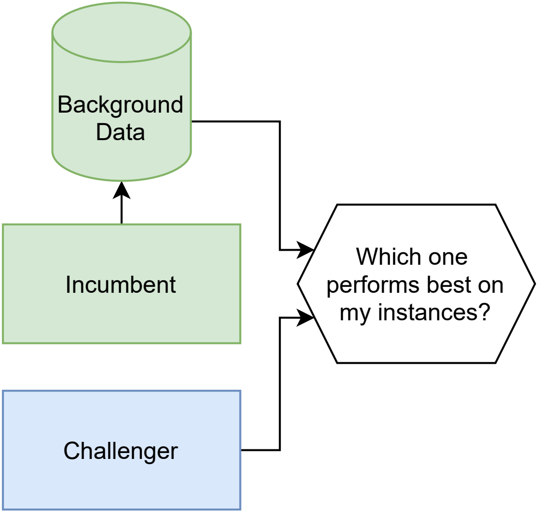

min CPU time
max accuracy

Iterative Strategy

```
compute instances score
```

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while confidence < threshold do
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Iterative Strategy

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while confidence $<$ threshold **do**
    pick best instance according to score
    run challenger on that instance

Iterative Strategy

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compute instances score
while confidence < threshold do
    pick best instance according to score
    run challenger on that instance
    update confidence
    update instances score
end while
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while confidence < threshold do
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return best performing algorithm
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Score & Confidence Methods

Instance scores:

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- distribution-based: $\mathbb{P}(\underbrace{\sum_I \Delta T_I}_{\text{rand. var.}} + \underbrace{\sum_I \Delta t_I}_{\text{constant}} \leq 0)$

Evaluation protocol

- SAT 2020 + 3 ASlib datasets (CSP MiniZinc, BNSL, SAT 2018) [Bischl et al., 2016]

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- Report
  - % of CPU time
  - % of accuracy

Research Questions

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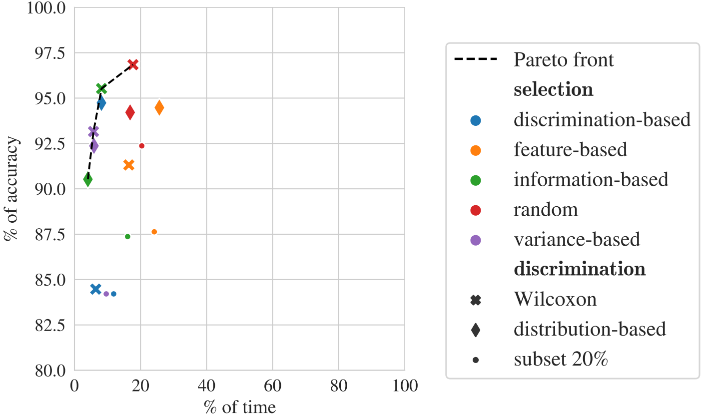
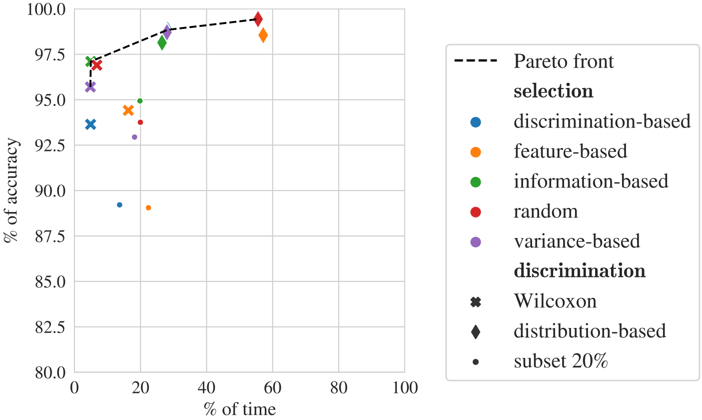
- Can our strategies discriminate well between top ranking algorithms?
- How do the selection methods affect the accuracy of the strategies?

Accuracy over Median Running Time



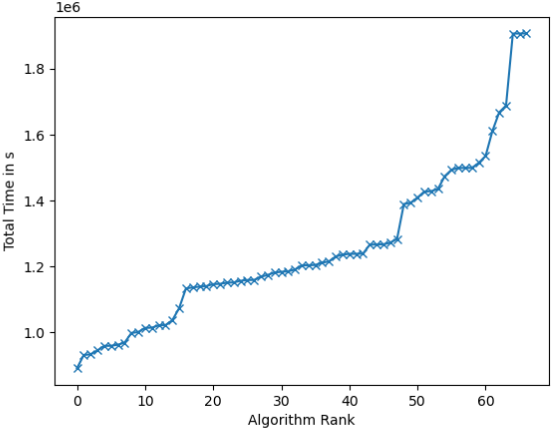
CSP MiniZinc [Stuckey et al., 2014] Confidence > 95%

Accuracy over Median Running Time



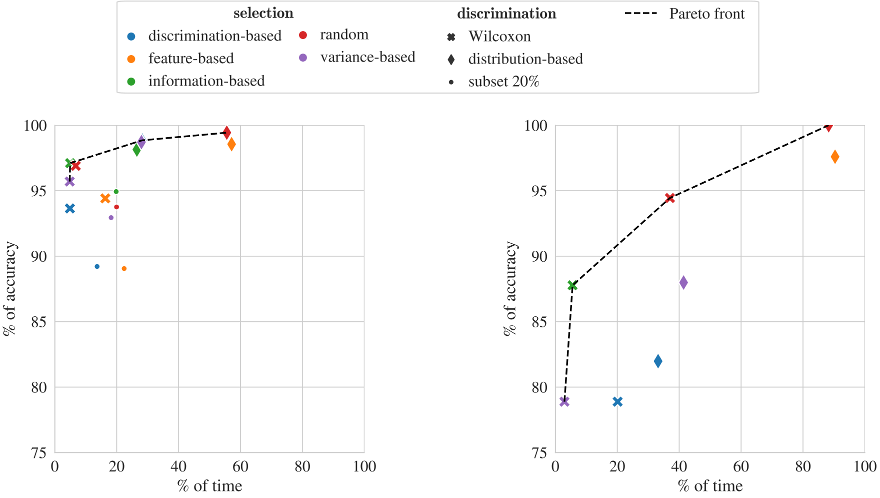
SAT 20 [Balyo et al., 2020]   Confidence > 95%

SAT 2020 Running Times



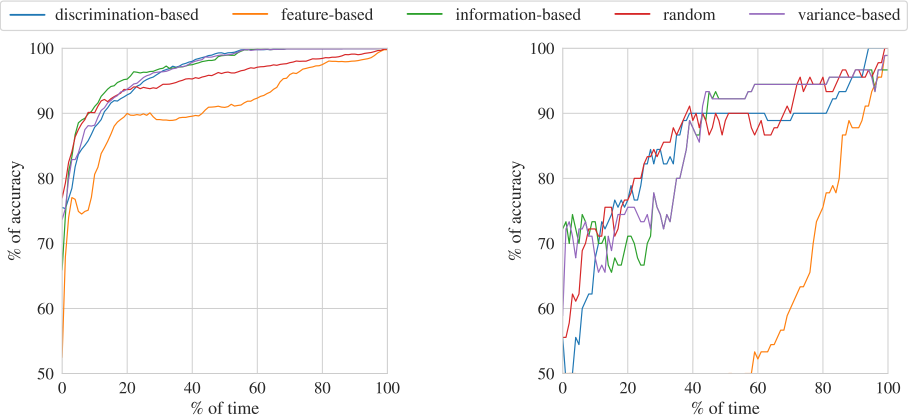
SAT 20 Algorithm Ranking

Top Ranking Algorithms



SAT 20 Confidence > 95% SAT 20, top-10

Selection Methods Accuracy for Wilcoxon



SAT 20

SAT 20, top-10

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`github.com/Theomat/PSEAS`

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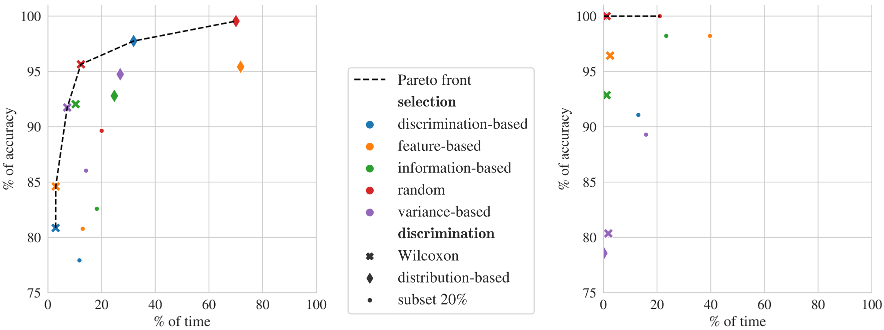

SAT 18

BNSL

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