

RANKING ROBUSTNESS UNDER SUB-SAMPLING FOR THE SAT COMPETITION 2018



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Motivation & Goals

- Benchmarks of SAT competition:
 - To rank solvers of competition
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 - To rank solvers of competition
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- Impact of benchmark selection on the final ranking?
 - Measure the robustness of the produced ranking of the competition
 - Range of sub-sampling strategies

INTRODUCTION



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- 400 brand new problems are selected
- At most 20 from the same source
- Same 400 instances used on Parallel and No-limits tracks

Random Sampling & Ranking Robustness

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■ Ranking Robustness

- Subsets of instances yield similar rankings

Spearman's rank correlation

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$$\rho(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \text{ where } d_i = \text{rank}(x_i) - \text{rank}(y_i)$$

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- Indicates how well the statistical dependence between two rank variables can be described using a monotonic function

Spearman's rank correlation

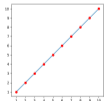
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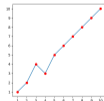
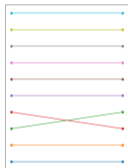
- Indicates how well the statistical dependence between two rank variables can be described using a monotonic function
- High when solvers have a similar rank

Spearman's correlation examples (1)

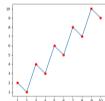
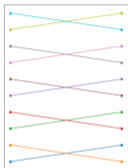
1.0



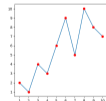
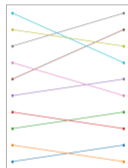
0.988



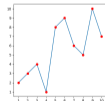
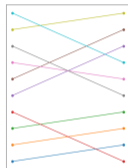
0.939



0.806

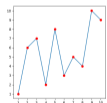
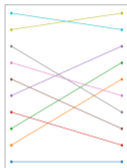


0.697

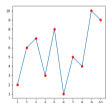
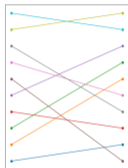


Spearman's correlation examples (2)

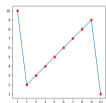
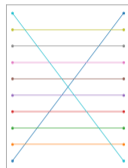
0.539



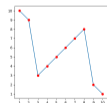
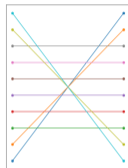
0.455



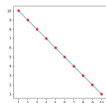
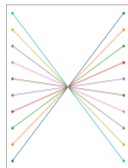
0.018



-0.576



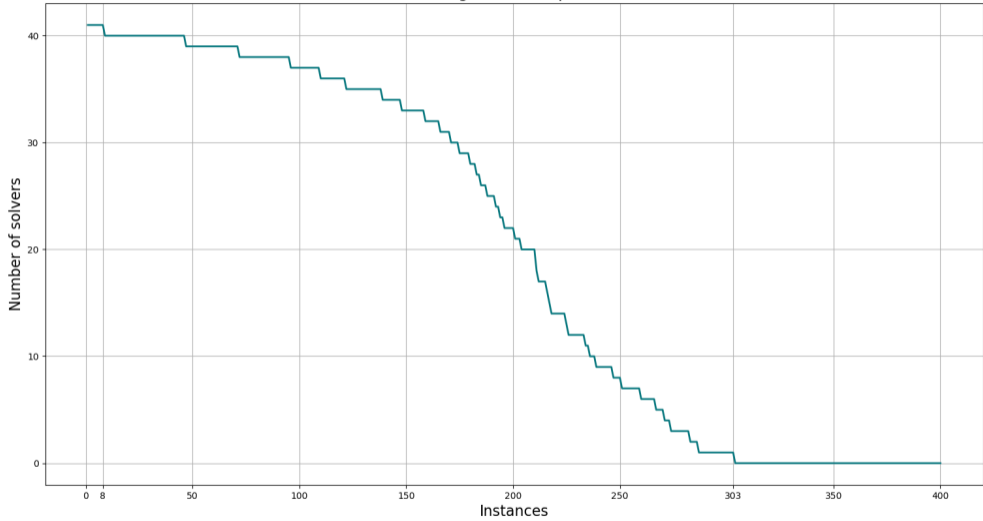
-1.0



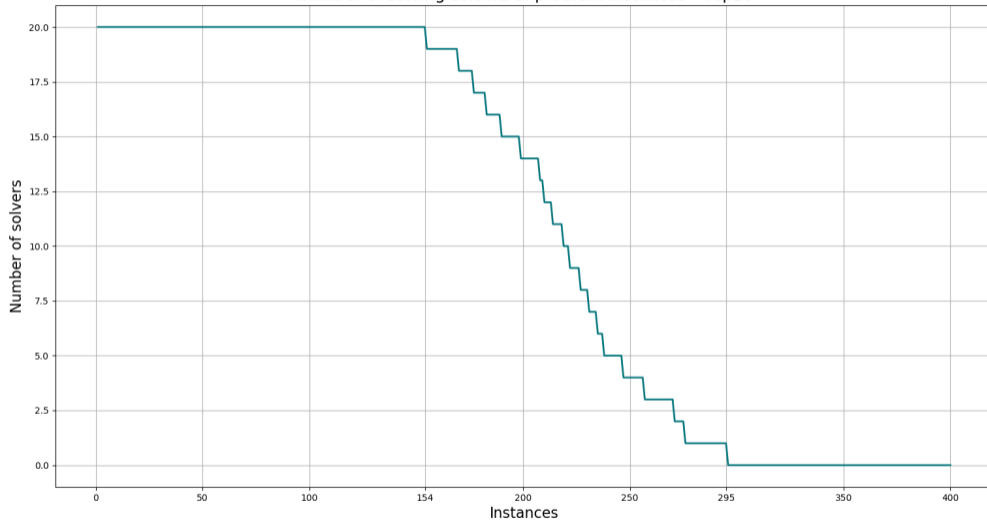
RANKING ROBUSTNESS UNDER RANDOM SAMPLING



Number of solving solvers of problem instances



Number of solving solvers of problem instances - Top20



Preprocessing – Data cleaning

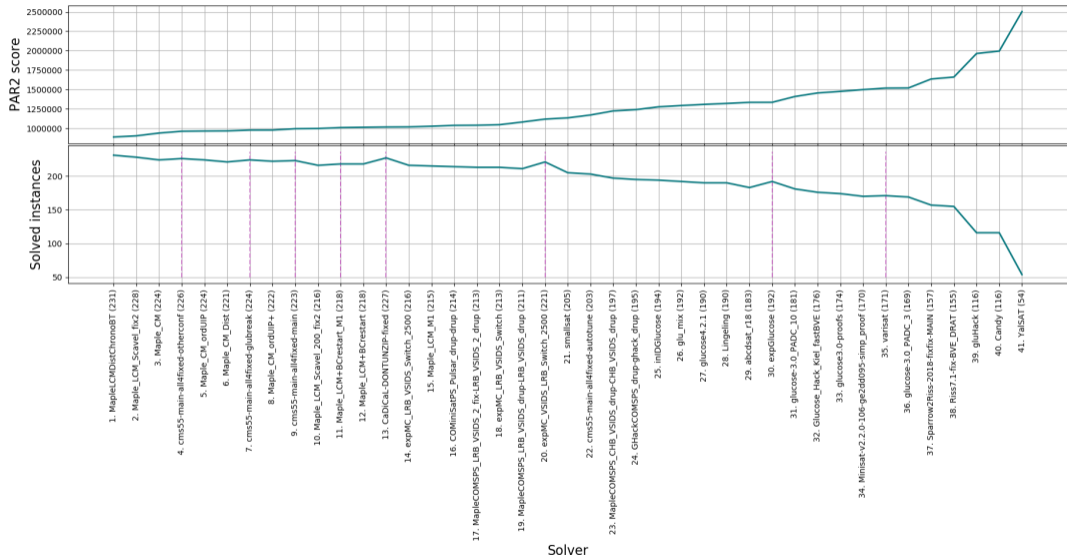
- Remove unsolved instances
 - their removal yields a rank of solvers with correlation 1 to the competition rank

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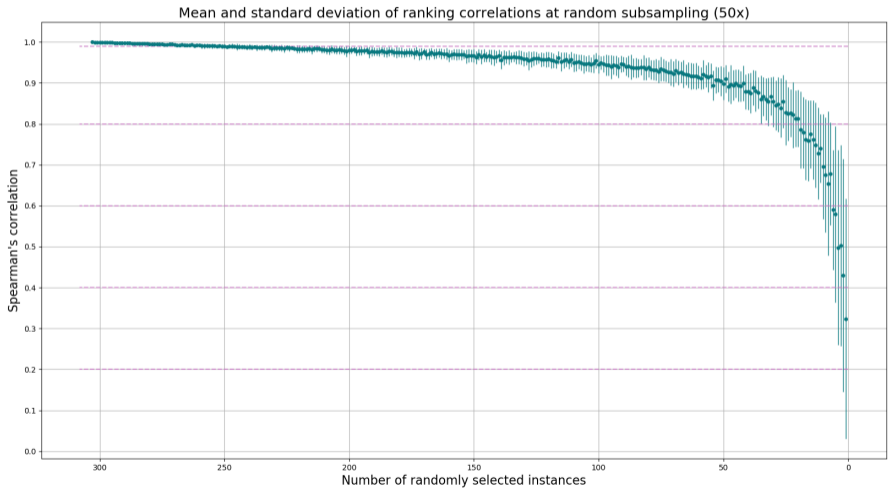
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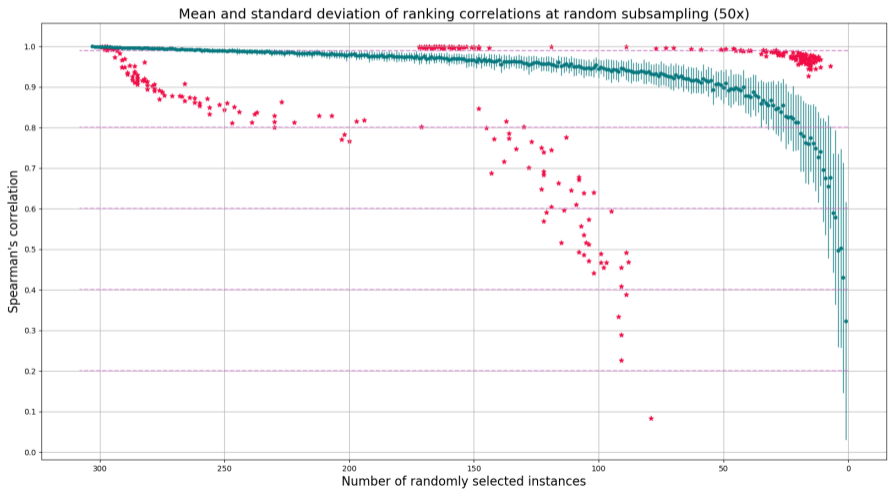
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 - `smallsat` solved but did not answer satisfiability
- Penalized time out even when satisfiability is answered
 - 5 instances (on one verification failed)



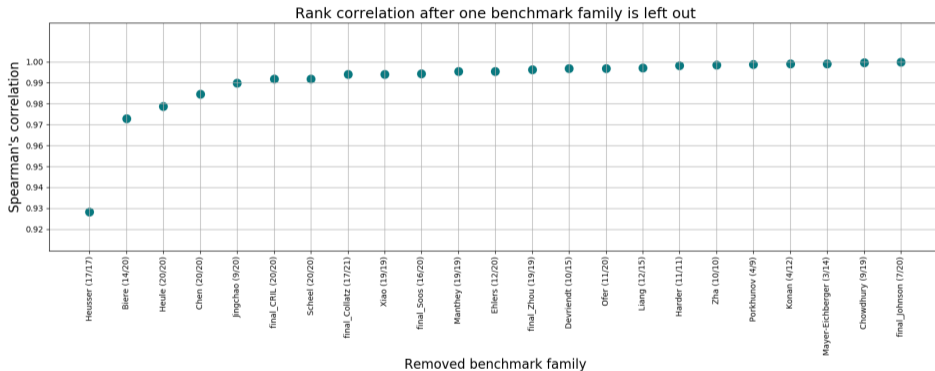
Ranking Robustness and Random sampling



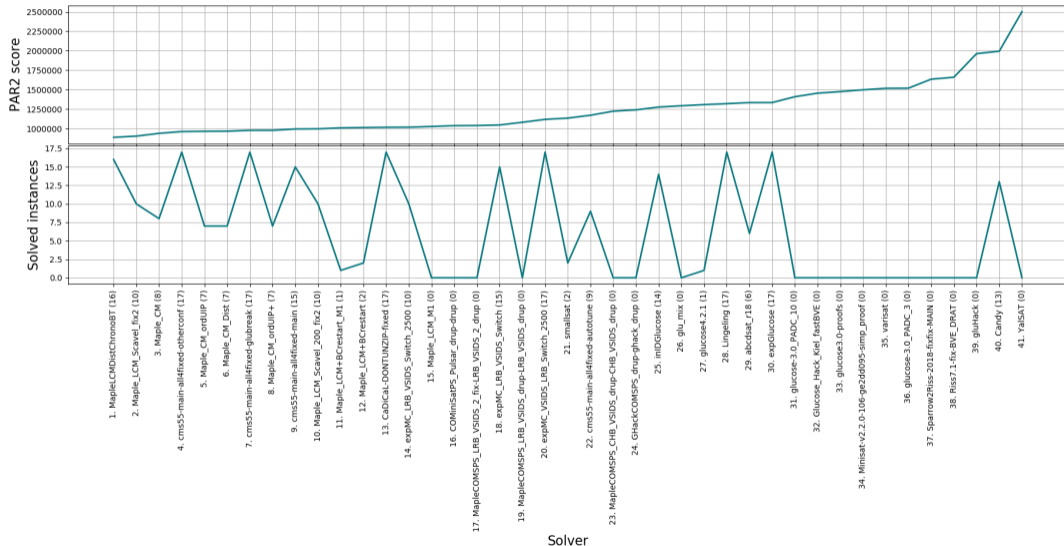
Ranking Robustness and GeneticAlg-Random sampling



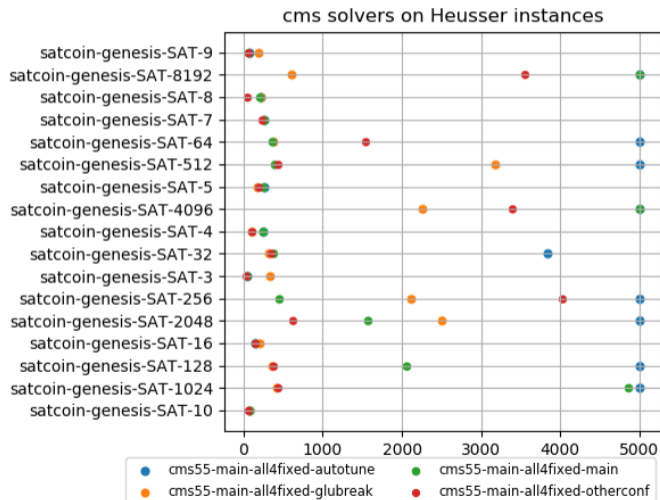
Ranking Robustness and Benchmark families



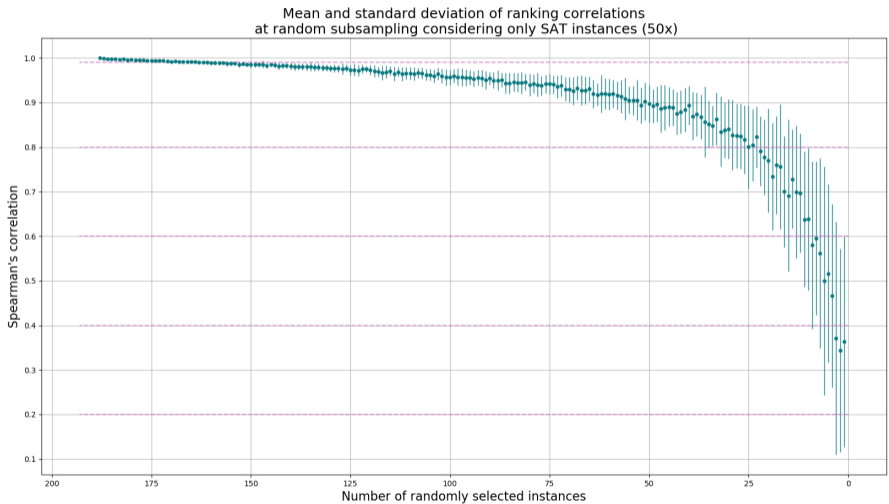
Ranking Robustness and Heusser benchmarks



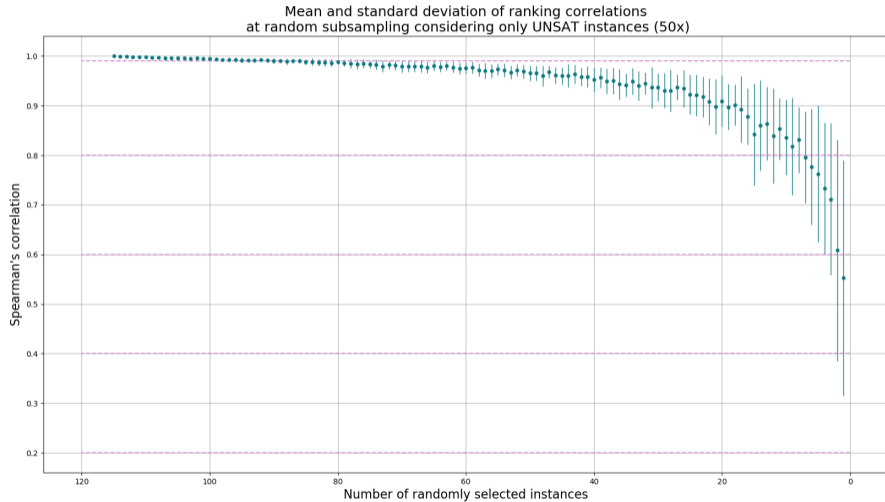
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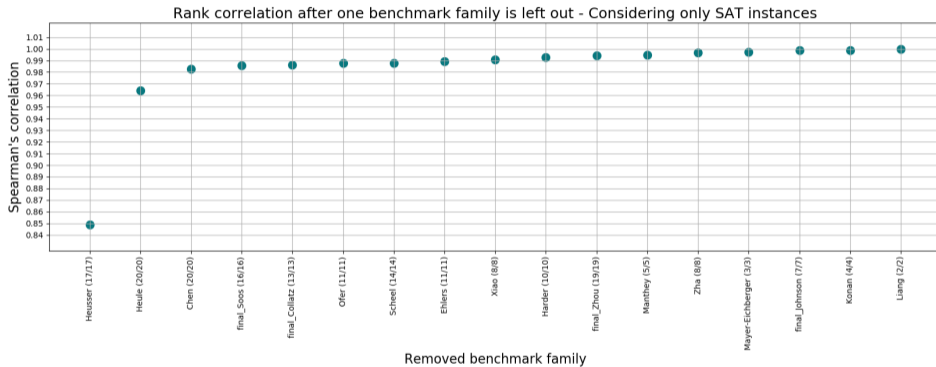
Ranking Robustness and Random sampling – SAT



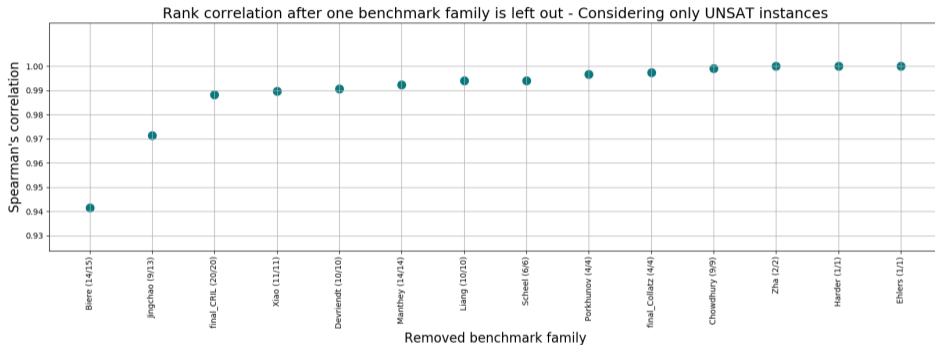
Ranking Robustness and Random sampling – UNSAT



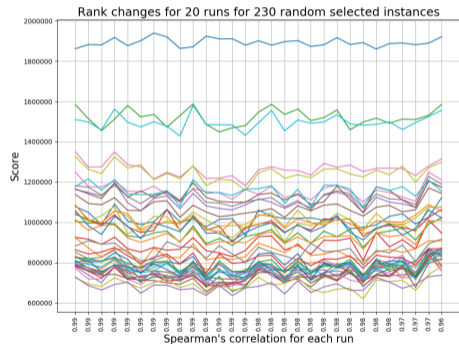
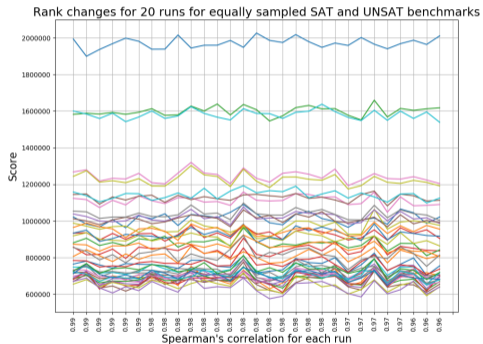
Ranking Robustness and Benchmark families – SAT



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Ranking Robustness and Satisfiability



CONCLUSION



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- Is the selection so good or the solvers so robust?

Thank you for your attention!