Choosing a Solver for Your Query An SVM-based Query Classification

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Instrs	Time(s)	TSolver(%)	Queries	[avgQT]
249643898	4201.31	95.66	449725	$9\mathrm{ms}$



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Which solver is the best?



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Choose Best Solver for Each Query



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Choose Best Solver for Each Query





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Solver Choice

Choose Best Solver for Each Query





Choose Best Solver for Each Query with Machine Learning





Choose Best Solver for Each Query with Machine Learning



Features

- size, domain and range of arrays
- operators, constants and variables in constraints
- occurrence of the latter in the query overall



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 - Identify more relevant properties of queries
 - ▶ Find reliable / stable training set





Per-Tool-Comparison





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Feature Set

Array features	Constraint features	Query features
Number of Arrays	Number of constraints	Constant count
Total size	Total constant count	Variable count
Maximum size	Maximum constant count	Operator count
Minimum size	Minimum constant count	Operator counts by
		type
Average size	Average constant count	
Maximum domain	Total variable count	
Minimum domain	Maximum variable count	
Average domain	Minimum variable count	
Maximum range	Average variable count	
Minimum range	Total operator count	
Average range	Maximum operator count	
	Minimum operator count	
	Average operator count	
	Operator counts by type	

