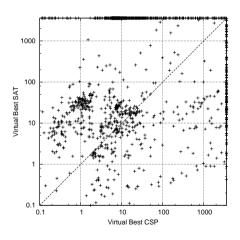
AutoML: Algorithm Selection Bonus: Combinatorial Problems

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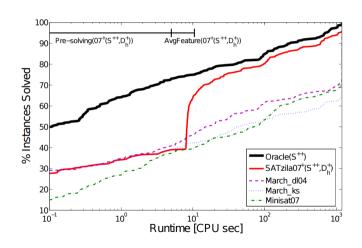
Motivation

- Algorithm Selection applied in many other domains
- success and performance improvements for combinatorial and optimization problems in Al dwarfs those in machine learning
- important application area of AI facilitating cross-disciplinary collaborations and advances

Motivation: Performance Differences [Barry et al. 2014]



Motivation: Leveraging the Differences [Xu et al. 2008]



Algorithms [Huberman et al. 1997]

- constraint solvers
- search strategies
- modeling choices
- different types of consistency

Features

- number of variables, number of clauses/constraints/...
- ratios
- order of variables/values
- connectivity clause/constraints-variable graph or variable graph
- number of nodes/propagations within time limit
- estimate of search space size
- tightness of problem/constraints
- . .

Example System – SATzilla [Xu et al. 2008]

- portfolio of 7 SAT solvers, trained on 4811 problem instances
- syntactic (33) and probing features (15)
- ridge regression to predict log runtime for each solver, choose the solver with the best predicted performance
- later version uses random forests to predict better algorithm for each pair, aggregation through simple voting scheme
- pre-solving, feature computation time prediction, hierarchical model, selection of algorithms to include in portfolio based on overall performance
- won several competitions

Benchmark library — ASlib [Bischl et al. 2015]

- https://github.com/coseal/aslib_data
- SAT, CSP, QBF, ASP, MAXSAT, OR, ML...
- includes data used frequently in the literature that you may want to evaluate your approach on
- more scenarios in the pipeline
- http://aslib.net

Tools

```
autofolio https://bitbucket.org/mlindauer/autofolio/
LLAMA https://bitbucket.org/lkotthoff/llama
SATzilla http://www.cs.ubc.ca/labs/beta/Projects/SATzilla/
```

(Much) More Information [Kotthoff. 2014]

Algorithm Selection Literature Summary Last update 21 November 2018								click headings to one click challens to expe		
	citation	domain	features	predict what	predict how	predict when	portfelio	,		
Langley 1860b, Langley	1863a	search	cast serformance	Monthly	hand-craffed and learned rules	office and online	Amanic	1		
Carbonell et al. 1991		planning	problem domain features, search statistics	control rules	explanation-based rule construction	arine	dynamic	1		
Gratch and DeJong 1993		planning	problem domain features, search statistics	control rules	probabilistic rule construction	onine	dynamic			
Smith and Swiff 1992		software design	features of abstract representation	algorithms and data structures	sinulated annealing	office	static	1		
Ana 1992		machine learning	instance features	elogration	learned rules	office	static			
Bradley 1983		machine learning	instance and algorithm features	elogrithm	hand-crafted rules	office	static			
Kemel et al. 1993		differential equations	pari performance, instance features	algorithm	hand-crafted rules	office	static			
Mirron 1960b, Mirron 19	80a, Minton 1986	CSP	runtime performance	algorithm	hand-crafted and learned rules	office	dynamic			
Cable 1994		sobsare design	instance features	algorithms and data structures	Farre-based knowledge base	office	Matic			
Trang et al. 1995		CSP	instance features				Madic			
Brewer 1985		software design	runtime performance	algorithms, data wouch,nes and their parameters	estistical model	office	Madic			
Weenwarana et al. 1996	, Joshi et al. 1996	differential equations	inelance features	runtime performance	Dayesian belief propagation, naural nets	office	static			
Borett et al. 1999		CSP	search statistics	Ewitch algorithm?	hand-craffed rules	anine	static, static order			
After and Minton 1999		SAT, CSP	probing	sustine performance	hand-crafted rules	onine	Matic			
Sakkout et al. 1990		CSP	search statistics	Ewitch algorithm?	hand-crafted rules	onine	Matic			
Huberman et al. 1997		graph calcuring	past performance	resource aflocation	etatistical model	office	Matic			
	So, Gornes and Seiman 1997's	CSP	problem size and past performance	algorithm	estistical model	office	Madic			
Cook and Varnell 1987		panellel search	proting	set of search strategies	decision trees. Bayesian classifier, nearest reighbour, neural net	onine	static			
First 1987, First 1998		planning	past performance	resource afocation	statistical model, regression	effice	state			
Lobjots and Lemaitre 101	6	branch and bound	probing	sustine performance	hand-craffed rules	entee	Matie			
Conewu et al. 1999		vehicle routing problem	runtime performance	algorithm	genetic algorithms	office	Matic			
Home et al. 1999		planning	Instance Features	resource afocation	Inear regression	effice	state			
Terashima-Marin et al. 11	108	scheduling	Instance and search features	algorithm	penetic algorithms	effice	dynamic			
Wilson et al. 2000		seftware design	iretance features	data structures	nearest neighbour	effine	state			
Beek and Pex 2000		jab shap scheduling	inelance feature changes during search	algorithm scheduling policy	hand-crafted rules	onine	static			
Brazdi and Soares 2000		classification	past performance	sanking	distribution model	office	Matic			
Lagoudakis and Litman	2000	order salection, sorting	inetance features	semaining coef for each sub- problem	HOP	anine	Madic			
588s 2908		CSP	probing	cest of solving problem	statistical model	effice	state			
Plahringer et al. 2000		elassification	inetance features, probing	algorithm	0 different classifiers	effice	state			
Fekunaga 2000		157	past performance	resource aflocation	performance simulation for different allocations	office	state			
Soares and Brazeli 2000		machine learning	instance features	tanking	nearest neighbour	office	Matic			
Gomes and Selman 200		CSP, mixed integer prognamming	part performance	algorithm	statistical model	offine	dynamic			
Petronic 2011	1. Epotein et al. 2002. Epotein et al. 2006. Epotein and	CEP	variable characteristics	algorithm	weights, hand-crafted rules	offine and online	dynamic			
Lagoudskie and Lithrean : Nameuell 2001	2001	DPLL branching rules autoritysten	instance features	nemaining cost for each sub- problem: expected utility of alcomitive.	HDP reinforcement learning	online office and online	static static			

http://larskotthoff.github.io/assurvey/