citation	domain	features	predict what	predict how	predict when	portfolio
[Langley; Langley]	search	past performance	algorithm	hand-crafted and learned rules	offline and online	dynamic
[Carbonell et al.]	planning	problem domain features, search statistics	control rules	explanation-based rule construction	online	dynamic
[Gratch and DeJong]	planning	problem domain features, search statistics	control rules	probabilistic rule construction	online	dynamic
[Smith and Setliff]	software design	features of abstract representation	algorithms and data structures	simulated annealing	offline	static
[Aha]	machine learning	instance features	algorithm	learned rules	offline	static
[Brodley]	machine learning	instance and algorithm features	algorithm	hand-crafted rules	offline	static
[Kamel et al.]	differential equations	past performance, instance features	algorithm	hand-crafted rules	offline	static
[Minton; Minton; Minton]	CSP	runtime performance	algorithm	hand-crafted and learned rules	offline	dynamic
[Cahill]	software design	instance features	algorithms and data structures	frame-based knowledge base	offline	static
[Tsang et al.]	CSP	instance features	-	-	-	static
[Brewer]	software design	runtime performance	algorithms, data structures and their parameters	statistical model	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Weerawarana et al.; Joshi et al.]	differential equations	instance features	runtime performance	Bayesian belief propagation, neural nets	offline	static
[Borrett et al.]	CSP	search statistics	switch algorithm?	hand-crafted rules	online	static, static order
[Allen and Minton]	SAT, CSP	probing	runtime performance	hand-crafted rules	online	static
[Sakkout et al.]	CSP	search statistics	switch algorithm?	hand-crafted rules	online	static
[Huberman et al.]	graph colouring	past performance	resource allocation	statistical model	offline	static
[Gomes and Selman; Gomes and Selman]	CSP	problem size and past performance	algorithm	statistical model	offline	static
[Cook and Varnell]	parallel search	probing	set of search strategies	decision trees, Bayesian classifier, nearest neighbour, neural net	online	static
[Fink; Fink]	planning	past performance	resource allocation	statistical model, regression	offline	static
[Lobjois and Lemaître]	branch and bound	probing	runtime performance	hand-crafted rules	online	static
[Caseau et al.]	vehicle routing problem	runtime performance	algorithm	genetic algorithms	offline	static
[Howe et al.]	planning	instance features	resource allocation	linear regression	offline	static
[Terashima-Marín et al.]	scheduling	instance and search features	algorithm	genetic algorithms	offline	dynamic

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citation	domain	features	predict what	predict how	predict when	portfolio
[Wilson et al.]	software design	instance features	data structures	nearest neighbour	offline	static
[Beck and Fox]	job shop scheduling	instance feature changes during search	algorithm scheduling policy	hand-crafted rules	online	static
[Brazdil and Soares]	classification	past performance	ranking	distribution model	offline	static
[Lagoudakis and Littman]	order selection, sorting	instance features	remaining cost for each sub-problem	MDP	online	static
[Sillito]	CSP	probing	cost of solving problem	statistical model	offline	static
[Pfahringer et al.]	classification	instance features, probing	algorithm	9 different classifiers	offline	static
[Fukunaga]	TSP	past performance	resource allocation	performance simulation for different allocations	offline	static
[Soares and Brazdil]	machine learning	instance features	ranking	nearest neighbour	offline	static
[Gomes and Selman]	CSP, mixed integer programming	past performance	algorithm	statistical model	offline	dynamic
[Epstein and Freuder; Epstein et al.; Epstein et al.; Epstein and Petrovic]	CSP	variable characteristics	algorithm	weights, hand-crafted rules	offline and online	dynamic
[Lagoudakis and Littman]	DPLL branching rules	instance features	remaining cost for each sub-problem	MDP	online	static
[Nareyek]	optimization	search statistics	expected utility of algorithm	reinforcement learning	offline and online	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Horvitz et al.]	CSP	instance and instance generator features, search statistics	runtime performance, restart parameters	Bayesian model	offline and online	static
[Borrett and Tsang]	CSP	instance features, search statistics	redundant CSP to add	hand-crafted rules	offline	-
[Cowling et al.; Cowling et al.]	scheduling	past performance	algorithm	reinforcement learning	online	static
[Little et al.]	logic puzzles	instance graph features	instance model transformations for runtime performance	nearest neighbour	offline	-
[Petrovic and Qu]	scheduling	instance features	algorithm	case-based reasoning	offline	static
[Leyton-Brown et al.]	winner determination problem	instance features	instance hardness	several forms of regression	offline	static
[Fukunaga; Fukunaga]	SAT	variable characteristics	algorithm	genetic algorithms	offline	dynamic
[Yu et al.; Yu et al.; Yu and Rauchwerger]	parallel reduction algorithms	instance features	algorithm	decision trees, general linear regression	offline and online	static
[Ruan et al.]	SAT	instance features	restart policy	dynamic programming	offline	static
[Burke et al.]	scheduling	past performance	algorithm	reinforcement learning	online	static
[Vrakas et al.]	planning	instance features	parameters	classification association rules	offline	dynamic

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citation	domain	features	predict what	predict how	predict when	portfolio
[Guo]	sorting, probabilistic inference	instance features	algorithm	decision tree, naïve Bayes, Bayesian network, meta-learning	offline	static
[Watson]	job shop scheduling	instance features, search statistics	local search algorithm	statistical model	offline and online	static
[Brazdil et al.]	machine learning	instance features	ranking	nearest neighbour	offline	static
[Gebruers et al.]	bid evaluation problem	instance and instance graph features	solution method	nearest neighbour	offline	static
[Guerri and Milano]	bid evaluation problem	instance and instance graph features	solution method, algorithm	decision trees	offline	static
[Beck and Freuder]	scheduling	probing	algorithm	hand-crafted rules	offline	static
[Nudelman et al.; Xu et al.; Xu et al.]	SAT	instance features, probing	runtime performance	ridge regression, lasso regression, SVMs, Gaussian processes	offline	static
[Carchrae and Beck; Carchrae and Beck]	job shop scheduling	probing, search statistics	length of exploration phase, switch algorithm?	Bayesian classifier, reinforcement learning	offline and online	static
[Soares et al.]	machine learning	instance features	ranking of SVM kernel widths	nearest neighbour	offline	static
[Guo and Hsu]	most probable explanation problem	instance features	algorithm	decision trees, naïve Bayes rules, Bayes networks, meta-learning techniques	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Gagliolo et al.]	search problems	past performance	resource allocation	linear model	online	static
[Prudêncio and Ludermir]	machine learning	instance features	ranking	decision trees and neural networks	offline	static
[Demmel et al.]	linear algebra	instance features	algorithm	multivariate Bayesian decision rule	offline	static
[Gebruers et al.]	CSP	instance features	problem model, solution strategy	nearest neighbour, decision trees, statistical model	offline	static
[Petrik]	SAT	past performance	resource allocation	analytic model, MDP	offline and online	static
[Cicirello and Smith]	scheduling	past performance	algorithm	reinforcement learning	online	static
[Gagliolo and Schmidhuber]	-	past performance	resource allocation	neural nets	online	static
[Gendreau and Potvin]	vehicle routing, scheduling	past performance	algorithm	various	online	static
[Armstrong et al.]	procedure calls	runtime performance	switch algorithm?	reinforcement learning	online	static
[Gagliolo and Schmidhuber]	SAT, auction winner determination problem	past performance	resource allocation	reinforcement learning	online	static
[Roberts and Howe]	planning	instance features	resource allocation	decision trees	offline	static
[Hough and Williams]	optimization	instance, algorithm and environment features	algorithm	ensembles of decision trees, SVMs	offline	static
[Bhowmick et al.]	linear systems	instance features	algorithm	boosting, alternating decision trees	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Hutter et al.]	stochastic local search	instance features	runtime performance	ridge regression	offline	dynamic
[Sayag et al.]	SAT	past performance	resource allocation	static model, probabilistic model	offline	static
[Ali and Smith]	classification	instance features	algorithm	decision rules	offline	static
[Cavazos and O'Boyle]	software design	instance features	algorithm	logistic regression	offline	static
[Burke et al.]	scheduling	instance features	algorithm	nearest neighbour	offline	static
[Xu et al.]	SAT	instance features	satisfiability and runtime performance	sparse multinomial logistic regression, ridge regression	offline	static
[Pulina and Tacchella; Pulina and Tacchella; Pulina and Tacchella]	QBF	instance features	resource allocation	decision trees, decision rules, logistic regression, nearest neighbour	offline and online	static
[Samulowitz and Memisevic]	QBF	instance features	algorithm, confidence values	multinomial logistic regression	offline and online	static
[Wu and van Beek]	scheduling	-	portfolio	case-based reasoning	offline	dynamic
[Streeter et al.]	planning	past performance	resource allocation	statistical model	offline and online	static
[Wang and Tropper]	simulation algorithms	past performance	control parameter	reinforcement learning	online	static
[Roberts and Howe; Roberts et al.]	planning	instance features	runtime, probability of success	32 different algorithms	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[de la Rosa et al.; de la Rosa et al.; de la Rosa et al.]	planning	instance features	algorithm	case-based reasoning	online	static
[Steer et al.]	-	fitness landscape features	algorithm	-	offline	static
[Streeter and Smith]	SAT, integer programming, planning	instance features	resource allocation	statistical model	offline and online	static
[O'Mahony et al.; Bridge et al.]	CSP	instance features, probing	resource allocation	nearest neighbour	offline	static
[Kuefler and Chen]	linear systems	instance features, search statistics	algorithm	reinforcement learning	online	static
[Wei et al.]	SAT	search statistics	algorithm	hand-crafted rules	online	static
[Gagliolo and Schmidhuber]	SAT	past performance	resource allocation	reinforcement learning	online	static
[Smith-Miles]	Quadratic Assignment Problem	instance features, probing	algorithm, runtime performance	neural networks and self-organising maps	offline	static
[Stergiou; Stergiou; Paparrizou and Stergiou]	CSP	search statistics	propagation method	clustering	online	static
[de la Rosa et al.; de la Rosa et al.]	planning	instance features	algorithm	decision tree	online	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Bai et al.]	resource allocation	past performance	combination of low-level heuristics	various	online	static
[Nikolić et al.]	SAT	instance features	search strategy	nearest neighbour	offline	static
[Stamatatos and Stergiou]	CSP	probing	propagation method	clustering	offline	static
[Arbelaez et al.; Arbelaez et al.]	CSP	instance features, search statistics	search strategy	SVM	online	static
[Haim and Walsh]	SAT	instance features	restart strategy and satisfiability	ridge regression, logistic regression	offline	static
[Bhowmick et al.]	linear systems	instance features	algorithm	nearest-neighbour, alternating decision trees, naïve Bayes, SVM	offline	static
[Gerevini et al.]	planning	past performance	macro actions, resource allocation	performance simulations for different allocations	offline	static
[Xu et al.]	CSP	instance features	algorithm	reinforcement learning	online	static
[Bougeret et al.]	SAT	past performance	resource allocation	static model	offline	static
[Smith-Miles et al.]	scheduling	instance features	algorithm	decision tree, neural networks, self-organizing maps	offline	static
[Leite et al.]	machine learning	past performance, probing	ranking of classification algorithms	statistical model	offline and online	static
[Silverthorn and Miikkulainen]	SAT	past performance	runtime performance	latent class models	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Stern et al.]	QBF, combinatorial auctions	instance and algorithm features	algorithm	Bayesian model	offline and online	static
[Garrido and Riff]	dynamic vehicle routing problem	runtime performance	combination of low-level heuristics	genetic algorithms	online	dynamic
[Domshlak et al.]	planning	state variables	algorithm	naïve Bayes classifier	online	static
[Kadioglu et al.]	SAT, mixed integer programming, set covering	instance features	algorithm	clustering	offline	dynamic
[Gent et al.]	CSP	instance features, probing	algorithm	decision trees	offline	static
[Gent et al.]	software design	instance features	implementation	19 different classifiers	offline	static
[Kotthoff et al.]	CSP	instance features, probing	algorithm	ensembles of classifiers	offline	static
[Ewald et al.]	simulation algorithms	past performance	portfolio	genetic algorithms	offline	dynamic
[Elsayed and Michel; Elsayed and Michel]	CSP	instance features	search strategy	hand-crafted rules	online	dynamic
[Valenzano et al.]	search problems	-	algorithm	round-robin	online	static
[Leite and Brazdil]	classification	past performance	ranking	statistical model	offline	static
[Aiguzhinov et al.]	classification	past performance	ranking	naïve Bayes	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Kanda et al.; Kanda et al.]	TSP	instance features	algorithms	nearest neighbour, decision tree, SVM, naïve Bayes	offline	static
[Peng et al.]	numerical optimization	past performance	resource allocation	optimization	offline	static
[Graff and Poli]	program induction	fitness function	runtime performance	regression	offline	static
[Fialho et al.]	genetic algorithms	past performance	algorithm	aggregation	online	static
[Burke et al.]	bin packing	past performance	combinations of low-level heuristics	genetic programming	online	static
[Tolpin and Shimony]	CSP	search statistics	algorithm	hand-crafted rules	online	static
[Malitsky et al.]	SAT	instance features	algorithm	nearest neighbour	offline	static
[Kadioglu et al.]	SAT	instance features	resource allocation	nearest neighbour	offline	static
[Kroer and Malitsky]	SAT, CSP	instance features	algorithm	clustering	offline	dynamic
[Kotthoff et al.; Kotthoff et al.]	SAT, QBF, CSP	instance features, probing	algorithm, runtime performance, ranking	31 different machine learning algorithms	offline	static
[Gagliolo and Schmidhuber; Gagliolo and Schmidhuber]	SAT, QBF, CSP	past performance	resource allocation	reinforcement learning	online	static
[Gebser et al.]	Answer Set Programming	instance features, probing	runtime performance	SVM	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Xu et al.]	MIP	instance features, probing	algorithm	random forests	offline	dynamic
[Maturana et al.]	evolutionary algorithms	past performance	algorithm	statistical models	online	static
[Helmert et al.]	planning	past performance	resource allocation	statistical model	offline	static
[Kiziltan et al.]	CSP	instance features	resource allocation	8 classification algorithms, ridge regression	offline	static
[Smith-Miles and Hemert]	TSP	instance features	algorithm	self-organizing map, decision tree, neural network	offline	static
[Prudêncio et al.]	machine learning	instance features	ranking	nearest neighbour	offline	static
[Hoffman et al.]	Bayesian Optimization	past performance	algorithm	multi-armed bandits	online	static
[Kotthoff]	SAT, QBF, CSP	instance features, probing	algorithm	5 regression algorithms, 2 classification algorithms	offline	static
[Yun and Epstein]	CSP	instance features	portfolio	case-based reasoning, hand-crafted rules	offline	dynamic
[Hurley and O'Sullivan]	SAT	instance features	ranking	case-based reasoning with voting	offline	static
[Shukla et al.]	inventory routing problem	past performance	portfolio	statistical model	offline	static
[Malitsky et al.]	SAT	past performance	resource allocation	nearest neighbour	offline and online	static
[Bischl et al.]	optimization	instance features	algorithm	SVM	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Veerapen et al.]	Quadratic Assignment Problem and TSP	past performance	algorithm	statistical model	online	static
[Valenzano et al.]	planning	past performance	resource allocation	statistical model	offline and online	static
[Hutter et al.; Hutter et al.]	SAT, MIP, TSP	instance features	algorithm performance	11 regression algorithms	offline	static
[Kanda et al.; Kanda et al.]	TSP	instance features	ranking	neural networks, nearest neighbour, clustering trees	offline	static
[Kadioglu et al.]	MIP	instance features	algorithm	clustering	online	static
[Seipp et al.]	planning	past performance	resource allocation	clustering and heuristic approaches	offline	static
[Maratea et al.; Maratea et al.]	ASP	instance features	algorithm	classification	offline	static
[Muñoz et al.]	optimization	instance features, algorithm parameters	runtime performance	neural network regression	offline	static
[Park et al.]	software design	instance features	runtime performance	SVM	offline	static
[Morak et al.]	ASP	instance features	algorithm	classification and regression	offline	static
[Burke et al.]	scheduling	past performance	algorithm	reinforcement learning	offline	static
[Pillay]	bin packing	past performance	combination of low-level heuristics	genetic algorithm	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Hu et al.]	evolutionary algorithms	past performance	algorithm	hand-crafted rule	online	static
[Sabharwal et al.]	SAT	instance features	resource allocation and switch algorithm?	nearest neighbour and decision tree classification	offline and online	static
[Abell et al.]	black-box optimization	instance features	algorithm	clustering	offline	static
[Hutter et al.]	SAT, MIP, TSP	instance features and algorithm parameters	algorithm performance	random forests, linear regression, neural networks, Gaussian processes, regression trees	offline	static
[Musliu and Schwengerer]	graph colouring	instance features	algorithm	six classifiers	offline	static
[Amadini et al.]	CSP	instance features	algorithm	range of different approaches	offline	static
[Alhossaini and Beck]	planning	instance features	model	SVM	offline	static
[Seijen et al.]	reinforcement learning	past performance	abstraction	MDP	online	static
[Malitsky et al.]	SAT	instance features	algorithm	clustering	online	static
[Mehta et al.]	CSP	instance features	algorithm	classification, regression and clustering	offline	static
[Malitsky et al.]	SAT	instance features	algorithm	classification	offline	static
[Rayner et al.]	combinatorial search	probing	subset of algorithms	optimization	offline	static
[Sun and Pfahringer]	machine learning	past performance	ranking	pairwise rules and trees	offline	static
[Collautti et al.]	SAT	instance features, past performance	algorithm	nearest neighbour, random forests	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Maratea et al.]	ASP	instance features	algorithm	PART decision rules	offline	static
[Wang et al.]	feature selection	instance features	algorithm	nearest neighbour and optimization	offline	static
[King et al.; King et al.]	power systems	instance features	algorithm	neural net, decision tree, random forest	offline	static
[Yuen et al.]	evolutionary algorithms	past performance	algorithm	linear regression	online	static
[Loth et al.]	CSP	past performance	algorithm	reinforcement learning	online	static
[Simon et al.]	software design	instance features	algorithm	neural networks, decision trees	offline	dynamic
[Geschwender et al.; Geschwender et al.]	CSP	instance features	algorithm	decision tree, neural network, naive Bayes	offline	static
[Nikolić et al.]	SAT	instance features	algorithm	nearest neighbour	offline	static
[Kendall and Li]	competitive TSP	instance features	algorithm	Bayesian approach	online	static
[Amadini et al.]	CSP	instance features	algorithm, resource allocation	5 different classifiers	offline and online	static
[Cauwet et al.]	optimization	past performance	resource allocation	statistical model	online	static
[Hoos et al.]	ASP, SAT, QBF, CSP	past performance	resource allocation	answer set programming	offline	static
[Hurley et al.]	CSP	instance features	instance representation, algorithm	classification, regression, clustering	offline	static
[Kotthoff]	CSP, SAT, QBF	instance features	ranking	classification, regression, meta-learning	offline	static
[Tang et al.]	numerical optimization	past performance	algorithm portfolio	optimization	offline	dynamic

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citation	domain	features	predict what	predict how	predict when	portfolio
[Fawcett et al.]	planning	instance features	runtime	regression	offline	static
[Amadini and Stuckey; Amadini et al.; Amadini et al.; Amadini et al.]	CSP	instance features	resource allocation	nearest neighbour	offline	static
[Blet et al.]	CSP	instance features	algorithm	M5P regression	offline	static
[Malitsky et al.]	Minimal Correction Subset	instance features, past performance	algorithm	nearest neighbour, random forests	offline	static
[Malitsky et al.]	Minimal Correction Subset	instance features	resource allocation	nearest neighbour, regression	offline	static
[Ansótegui et al.]	MaxSAT	instance features	algorithm	clustering	offline	static
[Malitsky and O'Sullivan]	CSP, MaxSAT, SAT	instance features, past performance	algorithm	random forest and linear regression	offline	static
[Smith et al.]	classification	past performance	algorithm	collaborative filtering	offline	static
[Garbajosa et al.]	planning	instance features	algorithm	classifier ensemble	online	static
[Pihera and Musliu]	TSP	instance features	algorithm	5 classifiers	offline	static
[St-Pierre and Teytaud]	Go	past performance	policy	static rule and reinforcement learning	offline and online	static
[van Rijn et al.]	machine learning	instance features	algorithm	decision stumps, random forests	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Lieder et al.]	sorting	instance features	performance	Bayesian regression	offline	static
[Lindauer]	ASP, CSP, SAT, QBF, OR	instance features	resource allocation	lots	offline	static
[Hoos et al.]	ASP	instance features	resource allocation	pairwise classification, regression, clustering	offline	static
[Sukhija et al.]	loop scheduling	instance features	algorithm	classification	offline	static
[Stojadinović and Marić]	CSP	instance features	algorithm	nearest neighbour	offline	static
[Shahriari et al.]	Bayesian Optimization	entropy	algorithm	multi-armed bandits	online	static
[López-Camacho et al.]	bin packing	instance features	algorithm	nearest neighbour	online	static
[Salcedo-Sanz et al.]	games	past performance	combination of low-level heuristics	genetic algorithm	offline	static
[Sagarna et al.]	software testing	instance features	algorithm	Bayesian network	offline	static
[Tierney and Malitsky]	container premarshalling	instance features, past performance	algorithm	hierarchical cost-sensitive clustering	offline	static
[Lindauer et al.]	SAT, QBF, ASP, container premarshalling	instance features	resource allocation	random forest pairwise classification, ridge regression, k-means clustering	offline	static
[Lindauer et al.; Lindauer et al.]	ASlib	instance features	resource allocation	pairwise classification, regression, clustering	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Kotthoff et al.]	TSP	instance features	algorithm	classification, regression, pairwise regression	offline	static
[Sabar and Kendall]	combinatorial search	past performance	algorithm	reinforcement learning	online	static
[Oentaryo et al.]	SAT	instance features and past performance	ranking	stochastic optimization	offline	static
[Chu and Stuckey]	CSP	instance features	algorithm	partial least squares regression	offline	static
[Balafrej et al.]	CSP	past performance	propagation method	multi-armed bandits	online	static
[Luo et al.]	stencil computation	instance features	solution space	multiple linear regression	offline	static
[Ilany and Gal]	multi-agent systems	instance features	runtime performance	linear regression, regression trees, neural network, multi-armed bandits	offline and online	static
[Everitt and Hutter; Everitt and Hutter]	search	instance features	runtime performance	analytical model	offline	static
[Amadini et al.]	ASlib	instance features	resource allocation	nearest neighbour	offline	static
[Phillips et al.]	search	past performance	resource allocation	multi-armed bandits	online	static
[Abseher et al.]	tree decomposition	instance features	ranking	linear regression, nearest neighbour, regression trees, neural network, SVM	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Yuen et al.; Lou and Yuen; Yuen et al.]	black-box optimization	instance features	algorithm	nearest neighbour	offline	static
[Palmieri et al.]	constraint programming	past performance	algorithm	statistical test	online	static
[Inala et al.]	SMT	past performance	encoding	pattern matching	offline	dynamic
[Mendes et al.]	games	instance features	algorithm	various classifiers	offline	static
[Bontrager et al.]	games	instance features	algorithm	hierarchical clustering and decision trees	offline	static
[Koitz and Wotawa; Koitz and Wotawa; Koitz-Hristov and Wotawa]	abductive diagnosis	instance features	algorithm	various classifiers	offline	static
[Minot et al.]	sum coloring problem	instance features	algorithm	hand-crafted rule	offline	static
[Kotthoff et al.]	subgraph isomorphism	instance features	algorithm	classification, regression, pairwise classification and regression	offline	static
[Degroote et al.; Degroote et al.]	ASlib	instance features	algorithm	random forest regression	offline	static
[Gonard et al.]	ASlib	instance features	resource allocation	random forest and nearest neighbour regression	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Sidnev]	matrix multiplication, sorting, linear equations, FFT	instance features	runtime performance, algorithm	linear regression	offline	static
[Benatia et al.; Benatia et al.]	sparse matrix-vector multiplication	instance features	runtime performance	SVM, neural network	offline	static
[Dutt and Haritsa]	database query processing	instance features	resource allocation	optimization	offline	static
[Liberto et al.]	MIP	instance features, search statistics	algorithm	clustering	online	static
[Lindauer et al.]	ASlib	instance features	resource allocation	nearest neighbour	offline	static
[Khalil et al.]	MIP	instance features, search statistics	ranking	SVM	online	static
[Cenamor et al.]	planning	instance features	resource allocation	classification, regression	offline	static
[Cunha et al.; Cunha et al.; Cunha et al.]	recommender systems	instance features, probing	algorithm	classification	offline	static
[Cui et al.; Chu et al.]	evolutionary algorithms	instance features	ranking	nearest neighbour, neural network	online	static
[Cui et al.]	building energy optimization	instance features	ranking	neural network	offline	static
[Mısır and Sebag]	ASlib	instance and algorithm features	ranking	matrix completion	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Ansótegui et al.]	MaxSAT	instance features, past performance	algorithm	search	offline and online	dynamic
[Minot et al.]	sum coloring problem	instance features	algorithm	pairwise random regression forests	offline	static
[Zaharija et al.]	robotics	instance features	algorithm	hand-crafted rules	offline	static
[Wagner et al.]	minimum vertex cover	instance features	algorithm	pairwise classification, regression, clustering	offline	static
[Chen et al.]	SAT, MaxSAT	instance features	algorithm	multi-output learning	offline	static
[Khali et al.]	MIP	instance features, search statistics	algorithm	logistic regression	online	static
[Gnad et al.]	planning	probing	ranking	static rule	offline	static
[Fitzgerald and O'Sullivan]	CSP, SAT, combinatorial auctions	past performance	algorithm	reinforcement learning	online	static
[Beham et al.; Beham et al.]	Quadratic Assignment Problem	instance features, probing	ranking	nearest neighbour	offline	static
[Selvaraj and Nagarajan]	optical network design	instance features	algorithm	-	offline	static
[Cunha et al.]	recommender systems	instance features	ranking	nearest neighbour, naive Bayes, trees	offline	static
[Stephenson and Renz]	Angry Birds	instance features	ranking	classification	offline	static
[Li and Kendall]	games	past performance	algorithm	reinforcement learning	online	static
[He et al.]	black-box optimization	past performance	algorithm	Bayesian approach	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Fuentetaja et al.]	planning	past performance	instance representation, algorithm	optimization	offline	dynamic
[Jana et al.]	protein structure prediction	instance features	algorithm	hand-crafted rule	offline	static
[Jankee et al.]	black-box optimization	past performance	algorithm	bandit algorithms	offline	static
[Georges et al.]	MIP	instance features, probing	portfolio	classification, regression, boosting	offline	static and dynamic
[Silva et al.]	games	instance features	algorithm	logistic regression	online	dynamic
[Degroote et al.]	Generalized Assignment Problem	instance features	algorithm	random forest	offline	static
[Gudu et al.]	combinatorial auctions	instance features	algorithm	auto-sklearn	offline	static
[Elmandouh and Wassal]	formal verification	instance features	resource allocation	classification	offline	static
[Ansotegui et al.]	CSP	instance features	resource allocation	classification	offline	static
[Hoos et al.]	QBF	instance features	algorithm	autofolio	offline	static
[Nikolić et al.]	theorem proving	instance features	algorithm, runtime performance	classification, regression	offline	static
[Deng et al.]	classification	instance features	algorithm	clustering	offline	static
[Wang et al.]	CSP	instance features	algorithm	decision tree	offline	static
[Tripoul et al.]	pattern matching	simulation	constraint	hand-crafted model	online	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Pavelski et al.; Pavelski et al.]	flowshop	instance features	algorithm	decision trees, gradient boosting	offline	static
[Alcobaça et al.]	machine learning	instance features	algorithm	classification	offline	static
[Kerschke et al.]	TSP	instance features	algorithm	classification, regression	offline	static
[Loera et al.]	optimization	instance	algorithm	neural networks	offline	static
[Mantovani et al.]	machine learning	instance features	algorithm	classification	offline	static
[Abdulrahman et al.]	machine learning	instance features	algorithm	ranking	offline	static

Table I: Summary of the Algorithm Selection literature.

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