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]	constraints	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.]	constraints	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.]	constraints	search statistics	switch algorithm?	hand-crafted rules	online	static, static order
[Allen and Minton]	SAT, constraints	probing	runtime performance	hand-crafted rules	online	static
[Sakkout et al.]	constraints	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]	constraints	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]	constraints	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
[Gomes and Selman]	constraints, mixed integer programming	past performance	algorithm	statistical model	offline	dynamic
[Cowling et al.]	scheduling	instance features	algorithm	hand-crafted rules, weights	online	static
[Epstein and Freuder; Epstein et al.; Epstein et al.; Epstein and Petrovic]	constraints	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]	optimisation	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.]	constraints	instance and instance generator features, search statistics	runtime performance, restart parameters	Bayesian model	offline and online	static
[Borrett and Tsang]	constraints	instance features, search statistics	redundant constraints to add	hand-crafted rules	offline	-
[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
[Vrakas et al.]	planning	instance features	parameters	classification association rules	offline	dynamic
[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

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citation	domain	features	predict what	predict how	predict when	portfolio
[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
[Gagliolo et al.]	search problems	past performance	resource allocation	linear model	online	static
[Demmel et al.]	linear algebra	instance features	algorithm	multivariate Bayesian decision rule	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Gebruers et al.]	constraints	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
[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]	optimisation	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
[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
[Xu et al.]	SAT	instance features	satisfiability and runtime performance	sparse multinomial logistic regression, ridge regression	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[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
[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.]	constraints	instance features, probing	resource allocation	nearest neighbour	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[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]	constraints	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
[Nikolić et al.]	SAT	instance features	search strategy	nearest neighbour	offline	static
[Stamatatos and Stergiou]	constraints	probing	propagation method	clustering	offline	static
[Arbelaez et al.; Arbelaez et al.]	constraints	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

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citation	domain	features	predict what	predict how	predict when	portfolio
[Gerevini et al.]	planning	past performance	macro actions, resource allocation	performance simulations for different allocations	offline	static
[Xu et al.]	constraints	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
[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.]	constraints	instance features, probing	algorithm	decision trees	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Gent et al.]	software design	instance features	implementation	19 different classifiers	offline	static
[Kotthoff et al.]	constraints	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]	constraints	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
[Kanda et al.; Kanda et al.]	TSP	instance features	algorithms	nearest neighbour, decision tree, SVM, naïve Bayes	offline	static
[Peng et al.]	numerical optimisation	past performance	resource allocation	optimisation	offline	static
[Graff and Poli]	program induction	fitness function	runtime performance	regression	offline	static
[Tolpin and Shimony]	constraints	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, constraints	instance features	algorithm	clustering	offline	dynamic

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citation	domain	features	predict what	predict how	predict when	portfolio
[Kotthoff et al.; Kotthoff et al.]	SAT, QBF, constraints	instance features, probing	algorithm, runtime performance, ranking	31 different Machine Learning algorithms	offline	static
[Gagliolo and Schmidhuber; Gagliolo and Schmidhuber]	SAT, QBF, constraints	past performance	resource allocation	reinforcement learning	online	static
[Gebser et al.]	Answer Set Programming	instance features, probing	runtime performance	SVM	offline	static
[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.]	constraints	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
[Kotthoff]	SAT, QBF, constraints	instance features, probing	algorithm	5 regression algorithms, 2 classification algorithms	offline	static
[Yun and Epstein]	constraints	instance features	portfolio	case-based reasoning, hand-crafted rules	offline	dynamic
[Hurley and OSullivan]	SAT	instance features	ranking	case-based reasoning with voting	offline	static
[Shukla et al.]	inventory routing problem	past performance	portfolio	statistical model	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Malitsky et al.]	SAT	past performance	resource allocation	nearest neighbour	offline and online	static
[Bischl et al.]	optimisation	instance features	algorithm	SVM	offline	static
[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.]	TSP	instance features	ranking	neural networks	offline	static
[Kadioglu et al.]	MIP	instance features	heuristic	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.]	optimisation	instance features, algorithm parameters	runtime performance	neural network regression	offline	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 optimisation	instance features	algorithm	clustering	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[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 coloring	instance features	algorithm	six classifiers	offline	static
[Amadini et al.]	constraints	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.]	constraints	instance features	algorithm	classification, regression and clustering	offline	static
[Malitsky et al.]	SAT	instance features	algorithm	clustering	offline	static
[Rayner et al.]	combinatorial search	probing	subset of algorithms	optimisation	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
[Maratea et al.]	ASP	instance features	algorithm	PART decision rules	offline	static
[Wang et al.]	feature selection	instance features	algorithm	nearest neighbour and optimisation	offline	static
[King et al.; King et al.]	power systems	instance features	algorithm	neural net, decision tree, random forest	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Yuen et al.]	evolutionary algorithms	past performance	algorithm	linear regression	online	static
[Amadini et al.]	constraints	instance features	algorithm, resource allocation	5 different classifiers	offline and online	static
[Cauwet et al.]	optimisation	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 encoding, algorithm	classification, regression, clustering	offline	static
[Kotthoff]	CSP, SAT, QBF	instance features	ranking	classification, regression, meta-learning	offline	static
[Tang et al.]	numerical optimisation	past performance	algorithm portfolio	optimisation	offline	dynamic
[Fawcett et al.]	planning	instance features	runtime	regression	offline	static
[Amadini and Stuckey]	COP	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

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citation	domain	features	predict what	predict how	predict when	portfolio
[Garbajosa et al.]	planning	instance features	algorithm	classifier ensemble	online	static
[Amadini et al.]	constraints	instance features	resource allocation	nearest neighbour	offline	static
[Pihera and Nysret]	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
[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
[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.]	aslib 1.0	instance features	resource allocation	pairwise classification, regression, clustering	offline	static
[Kotthoff et al.]	TSP	instance features	algorithm	classification, regression, pairwise regression	offline	static

Table I: Summary of the Algorithm Selection literature.

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