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	problem features	algorithm	learned rules	offline	static
[Brodley]	Machine Learning	problem and algorithm features	algorithm	hand-crafted rules	offline	static
[Kamel et al.]	differential equations	past performance, problem features	algorithm	hand-crafted rules	offline	static
[Minton; Minton; Minton]	constraints	runtime performance	algorithm	hand-crafted and learned rules	offline	dynamic
[Cahill]	software design	problem features	algorithms and data structures	frame-based knowledge base	offline	static
[Tsang et al.]	constraints	problem 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	problem 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	problem features	resource allocation	linear regression	offline	static
[Terashima-Marín et al.]	scheduling	problem 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	problem features	data structures	nearest neighbour	offline	static
[Beck and Fox]	job shop scheduling	problem 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	problem 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	problem 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	problem 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	problem 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	problem and problem generator features, search statistics	runtime performance, restart parameters	Bayesian model	offline and online	static
[Borrett and Tsang]	constraints	problem features, search statistics	redundant constraints to add	hand-crafted rules	offline	-
[Little et al.]	logic puzzles	problem graph features	problem model transformations for runtime performance	nearest neighbour	offline	-
[Petrovic and Qu]	scheduling	problem features	algorithm	case-based reasoning	offline	static
[Leyton-Brown et al.]	winner determination problem	problem features	problem 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	problem features	algorithm	decision trees, general linear regression	offline and online	static
[Vrakas et al.]	planning	problem features	parameters	classification association rules	offline	dynamic
[Guo]	sorting, probabilistic inference	problem features	algorithm	decision tree, naïve Bayes, Bayesian network, meta-learning	offline	static
[Watson]	job shop scheduling	problem features, search statistics	local search algorithm	statistical model	offline and online	static
[Brazdil et al.]	Machine Learning	problem features	ranking	nearest neighbour	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Gebruers et al.]	bid evaluation problem	problem and problem graph features	solution method	nearest neighbour	offline	static
[Guerri and Milano]	bid evaluation problem	problem and problem 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	problem 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	problem features	ranking of SVM kernel widths	nearest neighbour	offline	static
[Guo and Hsu]	most probable explanation problem	problem 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	problem features	algorithm	multivariate Bayesian decision rule	offline	static
[Gebruers et al.]	constraints	problem features	problem model, solution strategy	nearest neighbour, decision trees, statistical model	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[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	problem features	resource allocation	decision trees	offline	static
[Hough and Williams]	optimisation	problem, algorithm and environment features	algorithm	ensembles of decision trees, SVMs	offline	static
[Bhowmick et al.]	linear systems	problem features	algorithm	boosting, alternating decision trees	offline	static
[Hutter et al.]	stochastic local search	problem features	runtime performance	ridge regression	offline	dynamic
[Sayag et al.]	SAT	past performance	resource allocation	static model, probabilistic model	offline	static
[Xu et al.]	SAT	problem features	satisfiability and runtime performance	sparse multinomial logistic regression, ridge regression	offline	static
[Pulina and Tacchella; Pulina and Tacchella]	QBF	problem features	resource allocation	decision trees, decision rules, logistic regression, nearest neighbour	offline and online	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Samulowitz and Memisevic]	QBF	problem 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	problem features	runtime, probability of success	32 different algorithms	offline	static
[Streeter and Smith]	SAT, integer programming, planning	problem features	resource allocation	statistical model	offline and online	static
[O'Mahony et al.; Bridge et al.]	constraints	problem features, probing	resource allocation	nearest neighbour	offline	static
[Kuefler and Chen]	linear systems	problem 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	problem 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

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citation	domain	features	predict what	predict how	predict when	portfolio
[Nikolić et al.]	SAT	problem features	search strategy	nearest neighbour	offline	static
[Stamatatos and Stergiou]	constraints	probing	propagation method	clustering	offline	static
[Arbelaez et al.; Arbelaez et al.]	constraints	problem features, search statistics	search strategy	SVM	online	static
[Haim and Walsh]	SAT	problem features	restart strategy and satisfiability	ridge regression, logistic regression	offline	static
[Bhowmick et al.]	linear systems	problem 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.]	constraints	problem features	algorithm	reinforcement learning	online	static
[Bougeret et al.]	SAT	past performance	resource allocation	static model	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	problem 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

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citation	domain	features	predict what	predict how	predict when	portfolio
[Domshlak et al.]	planning	state variables	algorithm	naïve Bayes classifier	online	static
[Kadioglu et al.]	SAT, mixed integer programming, set covering	problem features	algorithm	clustering	offline	dynamic
[Gent et al.]	constraints	problem features, probing	algorithm	decision trees	offline	static
[Gent et al.]	software design	problem features	implementation	19 different classifiers	offline	static
[Kotthoff et al.]	constraints	problem 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	problem 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	problem features	algorithms	nearest neighbour, decision tree, SVM, naïve Bayes	offline	static
[Tolpin and Shimony]	constraints	search statistics	algorithm	hand-crafted rules	online	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Malitsky et al.]	SAT	problem features	algorithm	nearest neighbour	offline	static
[Kadioglu et al.]	SAT	problem features	resource allocation	nearest neighbour	offline	static
[Kroer and Malitsky]	SAT, constraints	problem features	algorithm	clustering	offline	dynamic
[Kotthoff et al.; Kotthoff et al.]	SAT, QBF, constraints	problem 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	problem features, probing	runtime performance	SVM	offline	static
[Xu et al.]	MIP	problem 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	problem features	resource allocation	8 classification algorithms, ridge regression	offline	static
[Smith-Miles and Hemert]	TSP	problem features	algorithm	self-organizing map, decision tree, neural network	offline	static
[Kotthoff]	SAT, QBF, constraints	problem features, probing	algorithm	5 regression algorithms, 2 classification algorithms	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Yun and Epstein]	constraints	problem features	portfolio	case-based reasoning, hand-crafted rules	offline	dynamic
[Hurley and OSullivan]	SAT	problem 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.]	optimisation problems	problem 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.]	SAT, MIP, TSP	problem features	algorithm performance	11 algorithms	offline	static
[Kanda et al.]	TSP	problem features	ranking	neural networks	offline	static
[Kadioglu et al.]	MIP	problem features	heuristic	clustering	online	static
[Sabharwal et al.]	SAT	problem features	resource allocation and switch algorithm?	nearest neighbour and decision tree classification	offline and online	static
[Abell et al.]	black-box optimisation	problem features	algorithm	clustering	offline	static
[Hutter et al.]	SAT, MIP, TSP	problem features and algorithm parameters	algorithm performance	random forests, linear regression, neural networks, Gaussian processes, regression trees	offline	static

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citation	domain	features	predict what	predict how	predict when	portfolio
[Musliu and Schwengerer]	graph coloring	problem features	algorithm	six classifiers	offline	static
[Amadini et al.]	constraints	problem features	algorithm	range of different approaches	offline	static
[Alhossaini and Beck]	planning	problem features	model	SVM	offline	static
[Seijen et al.]	reinforcement learning	past performance	abstraction	MDP	online	static
[Malitsky et al.]	SAT	problem features	algorithm	clustering	online	static
[Mehta et al.]	constraints	problem features	algorithm	classification, regression and clustering	offline	static
[Malitsky et al.]	SAT	problem features	algorithm	clustering	offline	static
[Rayner et al.]	combinatorial search	probing	subset of algorithms	optimisation problem	offline	static
[Sun and Pfahringer]	machine learning	past performance	ranking	pairwise rules and trees	offline	static
[Collautti et al.]	SAT	problem features, past performance	algorithm	clustering	offline	static
[Amadini et al.]	constraints	problem 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	problem features	problem encoding, algorithm	classification, regression, clustering	offline	static
[Kotthoff]	CSP, SAT, QBF	problem features	ranking	classification, regression, meta-learning	offline	static

Table I: Summary of the Algorithm Selection literature.

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