Application of AI to formal methods — an analysis of current trends

Supplementary material

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1 Tables for RQ 1

Table 1: Entries grouped by years

Year	Articles	Count
2019	[1–32]	32
2020	[33–80]	48
2021	[81–119]	39
2022	[120–170]	51
2023	[171–191]	21
Total		191

Table 2: Entries grouped by type of publication venue

Entry type	Articles	Count
Workshop/short paper	[3, 9, 11, 13, 32, 34, 36, 49, 56, 69, 75, 76, 86, 87, 93, 95, 99, 103, 105, 123, 125, 137, 150, 154, 160, 164, 175, 176, 189]	29
Conference paper	[1, 2, 5, 7, 8, 10, 14, 15, 18–20, 23–30, 33, 35, 37, 39–41, 43, 47, 48, 51–55, 57–59, 61–66, 68, 70–74, 77–80, 82–85, 88–92, 94, 100–102, 106–120, 122, 124, 127, 129–136, 138, 140–146, 148, 149, 151, 153, 155, 157, 161–163, 165–169, 172, 173, 179–182, 184, 187, 188, 190, 191]	124
Journal paper	[4, 6, 12, 16, 17, 21, 22, 31, 38, 42, 44–46, 50, 60, 67, 81, 96–98, 104, 126, 128, 139, 147, 152, 156, 158, 159, 170, 171, 174, 177, 178, 183, 185, 186]	37
Book chapter	[121]	1
Total		191

Table 3: Overview of venues' respective research areas

Venue focus	Submissions
AI	94
Software Engineering	49
FM	40
Other	20
Automated Reasoning	19
Mathematics	8
Unique total	191

Table 4: Entries grouped by type of contribution

Contribution type	Articles	Count
Tool	[14, 23, 44, 46, 62, 69, 79, 95, 106, 109, 119, 129, 136, 180]	14
Tool improvement	[10, 15, 26, 48, 83, 88, 111, 122, 155, 172]	10
Idea	[165]	1
Approach	[19, 70]	2
Framework	[92, 114, 120, 128, 142, 167]	6

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Table 4: (Continued from previous page.)

Contribution type	Articles	Count
Methodology	[1, 3, 5, 7, 9, 11–13, 16–18, 20–22, 28, 30–32, 34, 36–38, 40–43, 45, 47, 49–51, 53–57, 60, 61, 63–65, 67, 68, 71, 73, 77, 78, 81, 82, 84–87, 89, 90, 93, 94, 96–99, 101–103, 105, 107, 108, 112, 115, 116, 118, 123, 124, 126, 127, 131–134, 139–141, 143–145, 147–154, 156, 157, 159–164, 168–171, 173–176, 178, 179, 182, 185–189, 191]	118
Case study	[121, 183]	2
Benchmark	[33, 39]	2
Training data	[2, 66, 72, 125, 158]	5
Mult. contributions	[4, 6, 8, 24, 25, 27, 29, 35, 52, 58, 74–76, 80, 91, 100, 104, 110, 113, 117, 130, 135, 137, 138, 146, 166, 177, 181, 190]	29
Total		189

Table 5: Entries grouped by type of contribution and publication venue

Contribution type	Entry type	Articles	Count
Tool	Workshop/short paper	[69, 95]	2
	Conference paper	[14, 23, 62, 79, 106, 109, 119, 129, 136, 180]	10
	Journal paper	[44, 46]	2
Tool improvement	Conference paper	[10, 15, 26, 48, 83, 88, 111, 122, 155, 172]	10
Idea	Conference paper	[165]	1
Approach	Conference paper	[19, 70]	2
Framework	Conference paper	[92, 114, 120, 142, 167]	5
	Journal paper	[128]	1
Methodology	Workshop/short paper	[3, 9, 11, 13, 32, 34, 36, 49, 56, 86, 87, 93, 99, 103, 105, 123, 150, 154, 160, 164, 175, 176, 189]	23

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Table 5: (Continued from previous page.)

Contribution type	Entry type	Articles	Count
	Conference paper	[1, 5, 7, 18, 20, 28, 30, 37, 40, 41, 43, 47, 51, 53–55, 57, 61, 63–65, 68, 71, 73, 77, 78, 82, 84, 85, 89, 90, 94, 101, 102, 107, 108, 112, 115, 116, 118, 124, 127, 131–134, 140, 141, 143–145, 148, 149, 151, 153, 157, 161–163, 168, 169, 173, 179, 182, 187, 188, 191]	67
	Journal paper	[12, 16, 17, 21, 22, 31, 38, 42, 45, 50, 60, 67, 81, 96–98, 126, 139, 147, 152, 156, 159, 170, 171, 174, 178, 185, 186]	28
Case study	Journal paper	[183]	1
	Book chapter	[121]	1
Benchmark	Conference paper	[33, 39]	2
Training data	Workshop/short paper	[125]	1
	Conference paper	[2, 66, 72]	3
	Journal paper	[158]	1
Mult. contributions	Workshop/short paper	[75, 76, 137]	3
	Conference paper	[8, 24, 25, 27, 29, 35, 52, 58, 74, 80, 91, 100, 110, 113, 117, 130, 135, 138, 146, 166, 181, 190]	22
	Journal paper	[4, 6, 104, 177]	4
Total			189

2 Tables for RQ 2

Table 6: Entries grouped by type of AI type used

AI technique	Articles	Count
DT	[3, 10, 15, 48, 115, 141, 144]	7
RF	[61, 124]	2
SVM	[67]	1
KNN	[35, 46]	2

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Table 6: (Continued from previous page.)

AI technique	Articles	Count
NN	[2, 9, 11, 14, 23–25, 27, 29, 30, 37–40, 43, 49, 52, 55, 62–66, 68, 69, 71, 74, 78, 80–83, 85, 90, 92, 95, 96, 105, 106, 110–113, 118, 121, 127–130, 133–135, 137, 138, 140, 146–148, 153, 161, 165, 167, 169, 172, 173, 175, 177, 180, 185, 189]	70
RL	[6, 17, 28, 32, 36, 47, 53, 54, 58, 73, 75, 79, 84, 99, 100, 102, 108, 114, 119, 131, 136, 139, 145, 155, 158, 168, 171, 176, 181, 183, 187, 190]	32
EA	[16, 18, 19, 22, 45, 94, 98, 107, 123, 132, 143, 152, 159, 179]	14
NLP	[44, 70, 72, 89, 91, 93, 101, 103, 125, 142, 151, 154, 160, 162–164]	16
Automaton learning	[76, 156]	2
Bayesian inference	[42, 51, 149]	3
Clustering	[12, 50, 166]	3
Data mining	[20, 60]	2
Mult. AI techniques	[4, 5, 7, 8, 13, 21, 26, 31, 33, 41, 56, 57, 86–88, 97, 104, 109, 117, 122, 126, 157, 170, 182, 186, 188, 191]	27
Custom	[1, 34, 77, 116, 120, 150, 174, 178]	8
Total		189

Table 7: Entries that use multiple AI types

AI technique	Articles	Count
RF	[4, 5, 21, 31, 33, 41, 57, 86, 117, 170, 186, 191]	12
SVM	[5, 26, 86, 104, 126, 170]	6
KNN	[21, 26, 86, 117, 170]	5
NN	[4, 7, 8, 33, 57, 87, 88, 97, 104, 122, 157, 182, 186]	13
EA	[97]	1
Clustering	[13, 56, 157]	3
Data mining	[41]	1
Logistic models	[4, 5, 21, 33, 126, 170]	6
LR	[21, 26, 86]	3
	[31]	1
Ridge regression	[86, 170, 186]	3
Naive bayes	[5, 33, 126, 170]	4
Trees	[4, 7, 13, 26, 31, 33, 56, 86, 88, 109, 117, 170]	12
Nearest centroid	[170]	1
Passive aggressive	[170]	1
Stochastic gradient	[170]	1
LLM	[188, 191]	2
Bagging	[26]	1
Adaboost	[26, 109]	2
Gaussian process	[170]	1
MCTS	[188]	1
SMAC	[13]	1
Unique total		27

Table 8: Entries grouped by AI types and contribution type

Contribution type	AI technique	Articles	Count
Tool	KNN	[46]	1
	NN	[14, 23, 62, 69, 95, 106, 129, 180]	8
	RL	[79, 119, 136]	3
	NLP	[44]	1
	Mult. AI techniques	[109]	1
Tool improvement	DT	[10, 15, 48]	3
	NN	[83, 111, 172]	3
	RL	[155]	1
	Mult. AI techniques	[26, 88, 122]	3
Idea	NN	[165]	1
Approach	EA	[19]	1
	NLP	[70]	1
Framework	NN	[92, 128, 167]	3
	RL	[114]	1
	NLP	[142]	1
	Custom	[120]	1
Methodology	DT	[3, 115, 141, 144]	4
	RF	[61, 124]	2
	SVM	[67]	1
	NN	[9, 11, 30, 37, 38, 40, 43, 49, 55, 63–65, 68, 71, 78, 81, 82, 85, 90, 96, 105, 112, 118, 127, 133, 134, 140, 147, 148, 153, 161, 169, 173, 175, 185, 189]	36
	RL	[17, 28, 32, 36, 47, 53, 54, 73, 84, 99, 102, 108, 131, 139, 145, 168, 171, 176, 187]	19
	EA	[16, 18, 22, 45, 94, 98, 107, 123, 132, 143, 152, 159, 179]	13
	NLP	[89, 93, 101, 103, 151, 154, 160, 162–164]	10
	Automaton learning	[156]	1
	Bayesian inference	[42, 51, 149]	3
	Clustering	[12, 50]	2
	Data mining	[20, 60]	2
	Mult. AI techniques	[5, 7, 13, 21, 31, 41, 56, 57, 86, 87, 97, 126, 157, 170, 182, 186, 188, 191]	18
	Custom	[1, 34, 77, 116, 150, 174, 178]	7
Case study	NN	[121]	1
	RL	[183]	1

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Table 8: (Continued from previous page.)

Contribution type	AI technique	Articles	Count
Benchmark	NN	[39]	1
	Mult. AI techniques	[33]	1
Training data	NN	[2, 66]	2
	RL	[158]	1
	NLP	[72, 125]	2
Mult. contributions	KNN	[35]	1
	NN	[24, 25, 27, 29, 52, 74, 80, 110, 113, 130, 135, 137, 138, 146, 177]	15
	RL	[6, 58, 75, 100, 181, 190]	6
	NLP	[91]	1
	Automaton learning	[76]	1
	Clustering	[166]	1
	Mult. AI techniques	[4, 8, 104, 117]	4
Total			189

Table 9: Entries grouped by AI types and publication years

AI technique	Year	Articles	Count
DT	2019	[3, 10, 15]	3
	2020	[48]	1
	2021	[115]	1
	2022	[141, 144]	2
RF	2020	[61]	1
	2022	[124]	1
SVM	2020	[67]	1
KNN	2020	[35, 46]	2
NN	2019	[2, 9, 11, 14, 23–25, 27, 29, 30]	10
	2020	[37–40, 43, 49, 52, 55, 62–66, 68, 69, 71, 74, 78, 80]	19
	2021	[81–83, 85, 90, 92, 95, 96, 105, 106, 110–113, 118]	15
	2022	[121, 127–130, 133–135, 137, 138, 140, 146–148, 153, 161, 165, 167, 169]	19
	2023	[172, 173, 175, 177, 180, 185, 189]	7
RL	2019	[6, 17, 28, 32]	4
	2020	[36, 47, 53, 54, 58, 73, 75, 79]	8
	2021	[84, 99, 100, 102, 108, 114, 119]	7
	2022	[131, 136, 139, 145, 155, 158, 168]	7

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Table 9: (Continued from previous page.)

AI technique	Year	Articles	Count
	2023	[171, 176, 181, 183, 187, 190]	6
EA	2019	[16, 18, 19, 22]	4
	2020	[45]	1
	2021	[94, 98, 107]	3
	2022	[123, 132, 143, 152, 159]	5
	2023	[179]	1
NLP	2020	[44, 70, 72]	3
	2021	[89, 91, 93, 101, 103]	5
	2022	[125, 142, 151, 154, 160, 162–164]	8
Automaton learning	2020	[76]	1
	2022	[156]	1
Bayesian inference	2020	[42, 51]	2
	2022	[149]	1
Clustering	2019	[12]	1
	2020	[50]	1
	2022	[166]	1
Data mining	2019	[20]	1
	2020	[60]	1
Mult. AI techniques	2019	[4, 5, 7, 8, 13, 21, 26, 31]	8
	2020	[33, 41, 56, 57]	4
	2021	[86–88, 97, 104, 109, 117]	7
	2022	[122, 126, 157, 170]	4
	2023	[182, 186, 188, 191]	4
Custom	2019	[1]	1
	2020	[34, 77]	2
	2021	[116]	1
	2022	[120, 150]	2
	2023	[174, 178]	2
Total			189

Table 10: Entries grouped by FM types

FM technique	Articles	Count
SAT	[1, 12, 17, 24–26, 28, 29, 33, 37, 39, 40, 45, 49, 50, 53–55, 57, 61, 67, 78, 80, 85, 96, 107, 115, 123, 124, 128, 131–133, 140, 146, 152, 153, 157, 165, 167, 168, 173, 174, 178, 189]	45
SMT	[3, 8, 41, 90, 100, 101, 108, 109, 116, 141, 176, 180, 186]	13

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Table 10: (Continued from previous page.)

FM technique	Articles	Count
TP	[2, 7, 9–11, 13–15, 19–21, 23, 27, 30, 32, 34–36, 42–44, 46–48, 52, 56, 58, 60, 62–66, 69, 72, 74–76, 79, 81–84, 87–89, 91, 97–99, 102, 104–106, 110, 111, 114, 117–119, 122, 130, 135, 137, 142, 144, 145, 147, 149, 150, 154, 155, 158, 160–164, 171, 172, 177, 183, 185, 188, 191]	85
MC	[16, 18, 22, 31, 51, 73, 86, 94, 113, 127, 136, 156, 159, 169, 170, 175, 179, 182]	18
Synthesis	[4, 5, 70, 77, 92, 93, 95, 103, 120, 125, 126, 129, 138, 139, 151, 166, 181, 187, 190]	19
Other	[6, 38, 68, 71, 112, 121, 134, 143, 148]	9
Total		189

Table 11: Entries grouped by TP application types

Application goal	Articles	Count
Heuristic selection	[13, 19]	2
Premise selection	[7, 10, 11, 15, 34, 43, 52, 56, 65, 82–84, 87–89, 98, 110, 118, 135, 142, 147, 149, 150, 158, 160, 161, 172]	27
Proof search	[2, 23, 32, 35, 42, 46, 48, 58, 64, 66, 69, 72, 79, 81, 97, 99, 119, 144, 155, 171, 188]	21
Proof mining	[60, 91]	2
Proof synthesis	[9, 27, 44, 47, 74, 76, 105, 106, 122, 130, 137, 145, 154, 163, 164, 177, 183, 185]	18
Symbolic	[102]	1
Formula synthesis	[36]	1
Formula classification	[104, 111]	2
Tactic prediction	[20, 30, 75, 117]	4
Lemma name generation	[62]	1
Portfolio solving	[21]	1
Mult. Techniques	[14, 63, 114, 162, 191]	5
Total		85

Table 12: Entries grouped by synthesis application types

Application goal	Articles	Count
Invariant learning	[92, 181, 187]	3

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Table 12: (Continued from previous page.)

Application goal	Articles	Count
Loop invariant learning	[77, 95, 166, 190]	4
Model repair	[4, 5, 126]	3
Models/Specification	[70, 93, 120, 125, 129, 138, 139, 151]	8
Annotations	[103]	1
Total		19

Table 13: Entries grouped by grade of TP automatization and TP application types

Application goal	Automation grade	Articles	Count
Heuristic selection	Automatic	[13, 19]	2
Premise selection	Interactive	[15]	1
	Automatic	[7, 10, 11, 34, 43, 52, 56, 65, 82–84, 87–89, 98, 110, 118, 135, 142, 147, 149, 150, 158, 160, 161, 172]	26
Proof search	Automatic	[2, 23, 32, 35, 42, 46, 48, 58, 64, 66, 69, 72, 79, 81, 97, 99, 119, 144, 155, 171, 188]	21
Proof mining	Interactive	[60]	1
	Automatic	[91]	1
Proof synthesis	Automatic	[9, 27, 44, 47, 74, 76, 105, 106, 122, 130, 137, 145, 154, 163, 164, 177, 183, 185]	18
Symbolic	Automatic	[102]	1
Formula synthesis	Automatic	[36]	1
Formula classification	Interactive	[111]	1
	Automatic	[104]	1
Tactic prediction	Interactive	[20, 75, 117]	3
	Automatic	[30]	1
Lemma name generation	Interactive	[62]	1
Portfolio solving	Automatic	[21]	1
Mult. Techniques	Interactive	[14, 114, 191]	3
	Automatic	[63]	1
	Mixed	[162]	1
Total			85

Table 14: Entries grouped by level of logic tackled by TP and TP application types

Application goal	Formalism	Articles	Count
Heuristic selection	FOL	[13]	1
	HOL	[19]	1
Premise selection	FOL	[7, 10, 11, 15, 34, 56, 65, 82–84, 87, 88, 110, 118, 135, 147, 149, 150, 158, 172]	20
	HOL	[43, 52, 89, 98, 142, 160, 161]	7
Proof search	FOL	[23, 42, 48, 66, 72, 79, 81, 171]	8
	HOL	[2, 32, 35, 46, 58, 64, 69, 97, 99, 119, 144, 155, 188]	13
Proof mining	HOL	[60, 91]	2
Proof synthesis	FOL	[9, 106, 122, 145, 154, 163, 164]	7
	HOL	[27, 44, 47, 74, 76, 105, 130, 137, 177, 183, 185]	11
Symbolic	HOL	[102]	1
Formula synthesis	HOL	[36]	1
Formula classification	FOL	[104, 111]	2
Tactic prediction	HOL	[20, 30, 75, 117]	4
Lemma name generation	HOL	[62]	1
Portfolio solving	HOL	[21]	1
Mult. Techniques	HOL	[14, 63, 114, 162, 191]	5
Total			85

Table 15: Entries grouped by FM techniques and years

FM technique	Year	Articles	Count
SAT	2019	[1, 12, 17, 24–26, 28, 29]	8
	2020	[33, 37, 39, 40, 45, 49, 50, 53–55, 57, 61, 67, 78, 80]	15
	2021	[85, 96, 107, 115]	4
	2022	[123, 124, 128, 131–133, 140, 146, 152, 153, 157, 165, 167, 168]	14
	2023	[173, 174, 178, 189]	4
SMT	2019	[3, 8]	2
	2020	[41]	1
	2021	[90, 100, 101, 108, 109, 116]	6
	2022	[141]	1
	2023	[176, 180, 186]	3
TP	2019	[2, 7, 9–11, 13–15, 19–21, 23, 27, 30, 32]	15
	2020	[34–36, 42–44, 46–48, 52, 56, 58, 60, 62–66, 69, 72, 74–76, 79]	24
	2021	[81–84, 87–89, 91, 97–99, 102, 104–106, 110, 111, 114, 117–119]	21
	2022	[122, 130, 135, 137, 142, 144, 145, 147, 149, 150, 154, 155, 158, 160–164]	18
	2023	[171, 172, 177, 183, 185, 188, 191]	7
MC	2019	[16, 18, 22, 31]	4
	2020	[51, 73]	2
	2021	[86, 94, 113]	3
	2022	[127, 136, 156, 159, 169, 170]	6
	2023	[175, 179, 182]	3
Synthesis	2019	[4, 5]	2
	2020	[70, 77]	2
	2021	[92, 93, 95, 103]	4
	2022	[120, 125, 126, 129, 138, 139, 151, 166]	8
	2023	[181, 187, 190]	3
Other	2019	[6]	1
	2020	[38, 68, 71]	3
	2021	[112]	1
	2022	[121, 134, 143, 148]	4
Total			189

Table 16: Entries grouped by FM techniques and contributions types

FM technique	Entry type	Articles	Count
SAT	Workshop/short paper	[49, 123, 189]	3

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Table 16: (Continued from previous page.)

FM technique	Entry type	Articles	Count
	Conference paper	[1, 24–26, 28, 29, 33, 37, 39, 40, 53–55, 57, 61, 78, 80, 85, 107, 115, 124, 131–133, 140, 146, 153, 157, 165, 167, 168, 173]	32
	Journal paper	[12, 17, 45, 50, 67, 96, 128, 152, 174, 178]	10
SMT	Workshop/short paper	[3, 176]	2
	Conference paper	[8, 41, 90, 100, 101, 108, 109, 116, 141, 180]	10
	Journal paper	[186]	1
TP	Workshop/short paper	[9, 11, 13, 32, 34, 36, 56, 69, 75, 76, 87, 99, 105, 137, 150, 154, 160, 164]	18
	Conference paper	[2, 7, 10, 14, 15, 19, 20, 23, 27, 30, 35, 43, 47, 48, 52, 58, 62–66, 72, 74, 79, 82–84, 88, 89, 91, 102, 106, 110, 111, 114, 117–119, 122, 130, 135, 142, 144, 145, 149, 155, 161–163, 172, 188, 191]	52
	Journal paper	[21, 42, 44, 46, 60, 81, 97, 98, 104, 147, 158, 171, 177, 183, 185]	15
MC	Workshop/short paper	[86, 175]	2
	Conference paper	[18, 51, 73, 94, 113, 127, 136, 169, 179, 182]	10
	Journal paper	[16, 22, 31, 156, 159, 170]	6
Synthesis	Workshop/short paper	[93, 95, 103, 125]	4
	Conference paper	[5, 70, 77, 92, 120, 129, 138, 151, 166, 181, 187, 190]	12
	Journal paper	[4, 126, 139]	3
Other	Conference paper	[68, 71, 112, 134, 143, 148]	6
	Journal paper	[6, 38]	2
	Book chapter	[121]	1
Total			189

Table 17: Entries grouped by FM and AI techniques

FM technique	AI technique	Articles	Count
SAT	DT	[115]	1
	RF	[61, 124]	2
	SVM	[67]	1

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Table 17: (Continued from previous page.)

FM technique	AI technique	Articles	Count
	NN	[24, 25, 29, 37, 39, 40, 49, 55, 78, 80, 85, 96, 128, 133, 140, 146, 153, 165, 167, 173, 189]	21
	RL	[17, 28, 53, 54, 131, 168]	6
	EA	[45, 107, 123, 132, 152]	5
	Clustering	[12, 50]	2
	Mult. AI techniques	[26, 33, 57, 157]	4
	Custom	[1, 174, 178]	3
SMT	DT	[3, 141]	2
	NN	[90, 180]	2
	RL	[100, 108, 176]	3
	NLP	[101]	1
	Mult. AI techniques	[8, 41, 109, 186]	4
	Custom	[116]	1
TP	DT	[10, 15, 48, 144]	4
	KNN	[35, 46]	2
	NN	[2, 9, 11, 14, 23, 27, 30, 43, 52, 62–66, 69, 74, 81–83, 105, 106, 110, 111, 118, 130, 135, 137, 147, 161, 172, 177, 185]	32
	RL	[32, 36, 47, 58, 75, 79, 84, 99, 102, 114, 119, 145, 155, 158, 171, 183]	16
	EA	[19, 98]	2
	NLP	[44, 72, 89, 91, 142, 154, 160, 162–164]	10
	Automaton learning	[76]	1
	Bayesian inference	[42, 149]	2
	Data mining	[20, 60]	2
	Mult. AI techniques	[7, 13, 21, 56, 87, 88, 97, 104, 117, 122, 188, 191]	12
	Custom	[34, 150]	2
MC	NN	[113, 127, 169, 175]	4
	RL	[73, 136]	2
	EA	[16, 18, 22, 94, 159, 179]	6
	Automaton learning	[156]	1
	Bayesian inference	[51]	1
	Mult. AI techniques	[31, 86, 170, 182]	4
Synthesis	NN	[92, 95, 129, 138]	4
	RL	[139, 181, 187, 190]	4
	NLP	[70, 93, 103, 125, 151]	5
	Clustering	[166]	1
	Mult. AI techniques	[4, 5, 126]	3

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Table 17: (Continued from previous page.)

FM technique	AI technique	Articles	Count
	Custom	[77, 120]	2
Other	NN	[38, 68, 71, 112, 121, 134, 148]	7
	RL	[6]	1
	EA	[143]	1
Total			189

Table 18: Entries grouped by TP and AI techniques

Application goal	AI technique	Articles	Count
Heuristic selection	EA	[19]	1
	Mult. AI techniques	[13]	1
Premise selection	DT	[10, 15]	2
	NN	[11, 43, 52, 65, 82, 83, 110, 118, 135, 147, 161, 172]	12
	RL	[84, 158]	2
	EA	[98]	1
	NLP	[89, 142, 160]	3
	Bayesian inference	[149]	1
	Mult. AI techniques	[7, 56, 87, 88]	4
	Custom	[34, 150]	2
Proof search	DT	[48, 144]	2
	KNN	[35, 46]	2
	NN	[2, 23, 64, 66, 69, 81]	6
	RL	[32, 58, 79, 99, 119, 155, 171]	7
	NLP	[72]	1
	Bayesian inference	[42]	1
	Mult. AI techniques	[97, 188]	2
Proof mining	NLP	[91]	1
	Data mining	[60]	1
Proof synthesis	NN	[9, 27, 74, 105, 106, 130, 137, 177, 185]	9
	RL	[47, 145, 183]	3
	NLP	[44, 154, 163, 164]	4
	Automaton learning	[76]	1
	Mult. AI techniques	[122]	1
Symbolic	RL	[102]	1
Formula synthesis	RL	[36]	1
Formula classification	NN	[111]	1

(Continued on next page.)

Table 18: (Continued from previous page.)

Application goal	AI technique	Articles	Count
	Mult. AI techniques	[104]	1
Tactic prediction	NN	[30]	1
	RL	[75]	1
	Data mining	[20]	1
	Mult. AI techniques	[117]	1
Lemma name generation	NN	[62]	1
Portfolio solving	Mult. AI techniques	[21]	1
Mult. Techniques	NN	[14, 63]	2
	RL	[114]	1
	NLP	[162]	1
	Mult. AI techniques	[191]	1
Total			85

Table 19: Entries grouped by SAT and AI techniques

Application goal	AI technique	Articles	Count
SAT solving	RF	[61]	1
	NN	[25, 80, 165, 167]	4
	RL	[28, 131]	2
	Mult. AI techniques	[33]	1
	Custom	[1]	1
Predict solvability	DT	[115]	1
	NN	[24, 37, 78, 128]	4
MaxSat	NN	[39, 96]	2
	RL	[17, 168]	2
	EA	[123, 132, 152]	3
	Custom	[178]	1
SAT parameter selection	RF	[124]	1
Branching heuristics	RL	[53]	1
	Mult. AI techniques	[57]	1
Algorithm/solver selection	RF	[61]	1
	SVM	[67]	1
	RL	[54, 131]	2
	Mult. AI techniques	[26, 157]	2
	Custom	[174]	1

(Continued on next page.)

Table 19: (Continued from previous page.)

Application goal	AI technique	Articles	Count
Instance selection	NN	[40, 49, 85, 173]	4
	Clustering	[12, 50]	2
Dependency analysis	NN	[189]	1
Meta analysis/performance prediction	NN	[55, 140, 153]	3
	EA	[45]	1
Generation	NN	[29, 133]	2
Mult. SAT tech	NN	[146]	1
	EA	[107]	1
Unique total			45

Table 20: Entries grouped by synthesis and AI techniques

Application goal	AI technique	Articles	Count
Invariant learning	NN	[92]	1
	RL	[181, 187]	2
Loop invariant learning	NN	[95]	1
	RL	[190]	1
	Clustering	[166]	1
	Custom	[77]	1
Model repair	Mult. AI techniques	[4, 5, 126]	3
Models/Specification	NN	[129, 138]	2
	RL	[139]	1
	NLP	[70, 93, 125, 151]	4
	Custom	[120]	1
Annotations	NLP	[103]	1
Total			19

Table 21: Datasets

FM	Articles	Count
SAT	[29]	1
SMT	[8]	1
TP	[2, 27, 35, 59, 66, 72, 74–76, 91, 104, 135, 137, 158, 184]	15
MC	[113]	1
Synthesis	[4, 125, 138]	3
Total		21

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