



Automated Planning

Performance: Planning competitions + Combining and tuning planners

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Planning Competitions

International Planning Competitions

- Started in 1998
 - Origin of the Planning Domain Definition Language
- Held irregularly, with different tracks
 - Rules have varied somewhat over time

Sequential Track Rules



Current rules (approximately):

Sequential Satisficing Track:

- For each problem instance, spend up to 30 minutes searching
- Return the highest quality (lowest cost) solution you found if you found one
- As long as you found it in 30 minutes, speed is irrelevant

Sequential Optimal Track:

- For each problem instance, spend up to 30 minutes searching
- Return an optimal solution or none at all
- Suboptimal in one domain → score 0 for that domain
- Suboptimal in *multiple* domains → disqualified

Sequential Agile Track:

- For each problem instance, spend up to 5 minutes searching
- Only speed counts: Return the first solution you find

IPC Scores: Satisficing

- Scores for satisficing planning:
 - Planner C, problem instance p

• score(C, p) =
$$\begin{cases} 0\\ \frac{\cos t \ of \ best \ solution}{\cos t \ of \ solution \ found \ by \ C} \end{cases}$$

if planner C did not solve p if planner C did solve p

- If the best cost found by any planner is 30, and you found a plan of cost 40, your score is 30/40 = 0.75
- Total score = sum of all individual problem instance scores



IPC Scores: Optimizing

- Scores for optimizing planning:
 - Planner C, problem instance p

•
$$score(C,p) = \begin{cases} 0 & if \ planner \ C \ did \ not \ solve \ p \\ 1 & if \ planner \ C \ did \ solve \ p \end{cases}$$



Our first results: 2008

IPC 2008



- International Planning Competition 2008:
 - First time that the domains were **secret**
 - First time that the experiments were **run by the organizers**
 - First time the performance scores were *clearly defined in advance*

Sequential Satisficing (1)



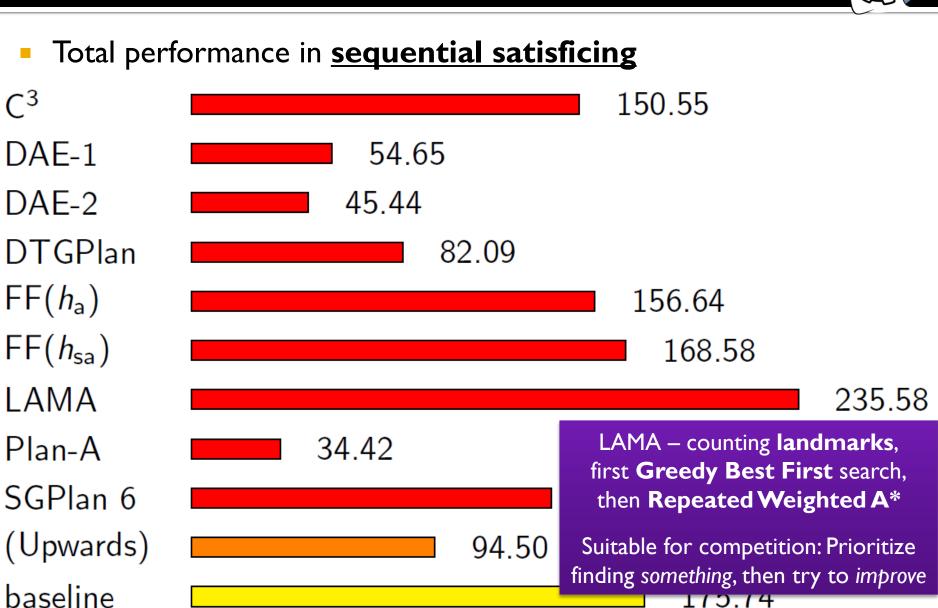
- Example performance per problem instance: OpenStacks domain
- Problem instance 1, 2, 3, ... C^3 DAE-1 Clear that planners are good at different things May solve larger instances but not smaller DAE-2 DTGPlan $FF(h_a)$ $FF(h_{sa})$ LAMA Plan-A SGPlan 6 (Upwards) baseline

Sequential Satisficing (2)

Example performance summarized for one domain





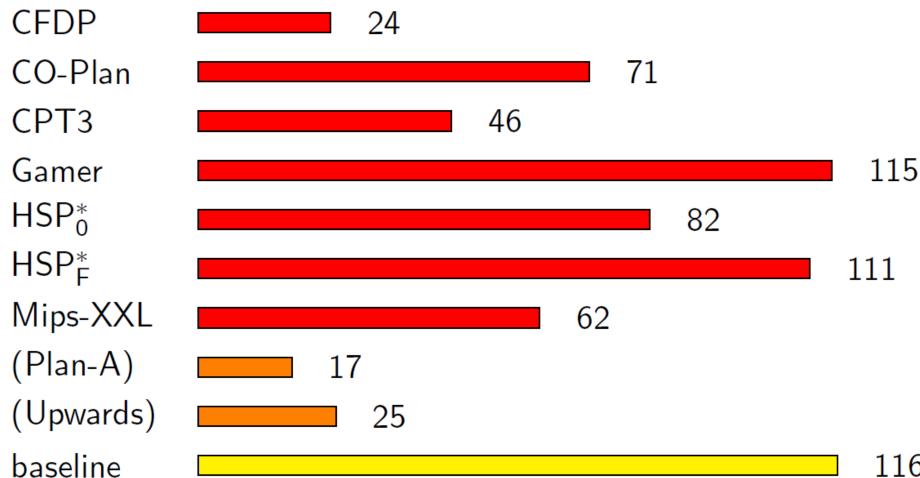


Sequential Satisficing (3)



Sequential Optimizing

Total performance in **sequential optimizing**





Parameter Optimization

Parameter Optimization (1)

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- Some planners have <u>many parameters</u> to tweak
 - In early planning competitions, domains were <u>known in advance</u>
 - Participants could manually adapt their "domain-independent" planners...
 - Somewhat <u>exaggerated quote</u> from IPC-2008 results:
 - if domain name begins with "PS" and part after first letter is "SR": use algorithm 100
 - else if there are 5 actions, all with 3 args, and 12 non-ground facts: use algorithm -1000
 - else if all facts ground and 10th/11th domain name letters "PA": use algorithm -1004
 - else if there are 11 actions and action name lengths range from 5 to 28: use algorithm 107

Parameter Optimization (2)



- How about *automatically* learning parameters?
 - One specific form of learning in planning others exist
 - Experimental application to <u>Fast Downward</u>
 - Optimization for speed: 45 params, 2.99 * 10¹³ possible configurations
 - Optimization for quality: 77 params, 1.94 * 10²⁶ possible configurations
 - Example parameters:
 - Heuristics used:
 - $h_{max} = h_0, h_m, h_{add}, h_{FF}, h_{LM}$ (landmarks), h_{LA} (admissible landmarks), goal count, ...
 - Method used to <u>combine heuristics</u>: Max, sum, selective max (learns which heuristic to use per state), tie-breaking, Pareto-optimal, alternation
 - Preferred operators used or not, for each heuristic
 - Like FF's helpful actions, but used for prioritization, not pruning
 - <u>Search strategy</u> combinations: Eager best-first, lazy best-first, EHC

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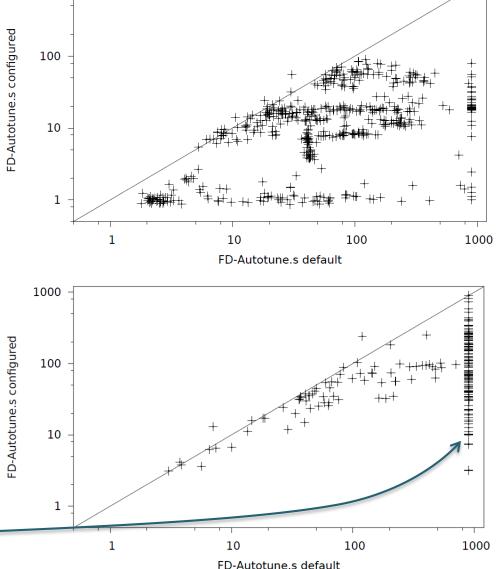
Parameter learning framework **ParamILS** used

Parameter Optimization (3): Results

1000

- <u>Under</u> the diagonal = <u>faster</u> than default configuration
 - For 540 small <u>training instances</u>:
 - Very good results
 - To be expected parameters tuned for these specific instances!
 - For 270 larger <u>test instances</u>:
 - From the same domains
 - Performance still improves

Unsolvable in 900 seconds by the default configuration



Parameter Optimization (4): Results

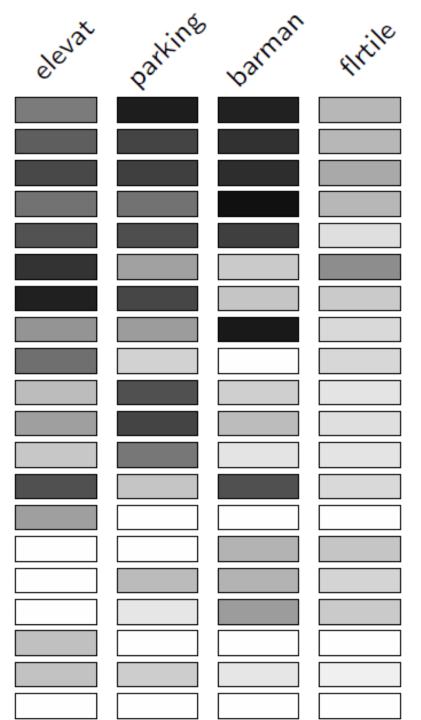
Complete results

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Sequential Satisficing track: Results

	Peesol	scaniz	Parcpri	opensi	nomys	*idybol	woodw	50Kopar.	trnspr	visitall	elevat	Parking	barman	FITTILE	
															lama-2011
															fdss-1
															fdss-2
															fd-autotune-1
															roamer
															fd-autotune-2
															forkuniform
															probe
better!															arvand
ē															lama-2008
															lamar
П															randward
															brt cbp2
Darker															daeyahsp
ar															yahsp2
\square															yahsp2-mt
															cbp
															lprpgp
															madagascar-p
															popf2
															madagascar
															cpt4
															satplanlm-c
															sharaabi
															acoplan
															acoplan2



lama-2011 fdss-1 fdss-2 fd-autotune-1 roamer fd-autotune-2 forkuniform probe arvand lama-2008 lamar randward brt cbp2 daeyahsp yahsp2 yahsp2-mt cbp lprpgp madagascar-p

Modified LAMA wins!

What's this? Let's see...

Two autotune variations, adapted to *older* domains (a few of which were still used)

Clear winner from 2008, now outrun by others

Portfolio Planners

Portfolio Planning (1)

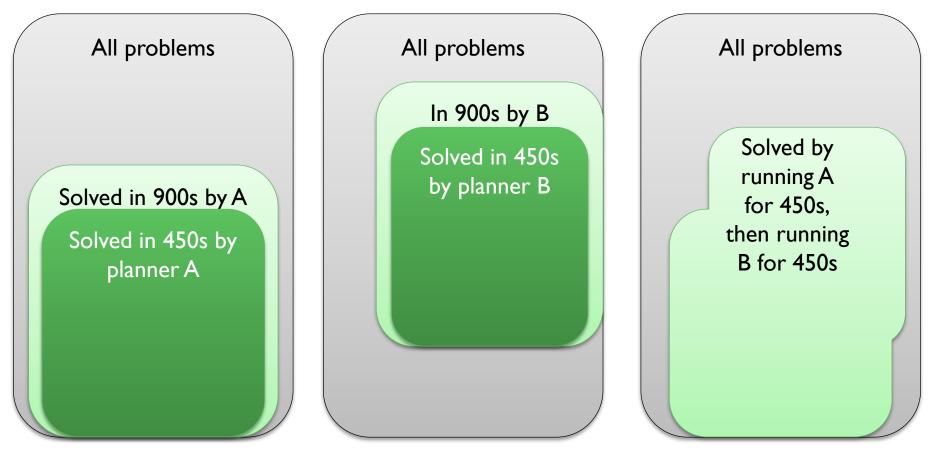
- Observation:
 - Different planners seem good in different domains!



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Portfolio Planning (2)

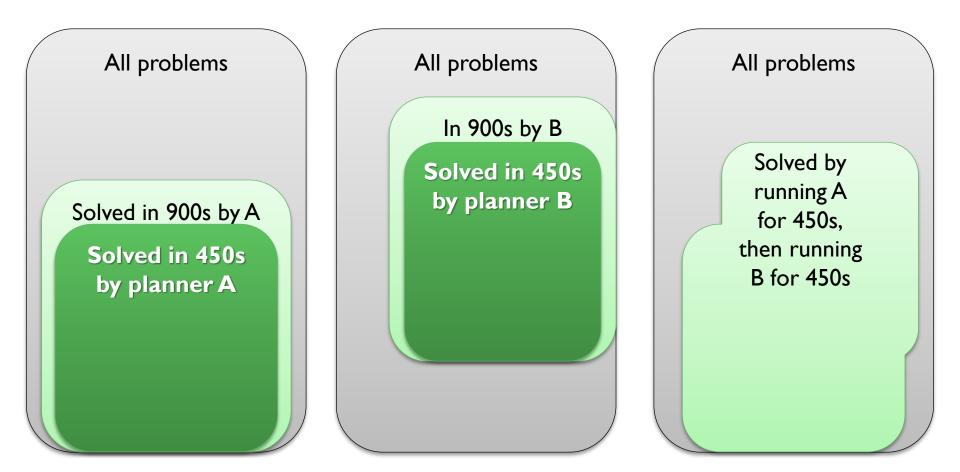
- Further analysis would show:
 - Even if two planners solve equally many problems in one domain, they may solve <u>different</u> problems
 - Also, planners often return plans <u>quickly</u> or <u>not at all</u>





Portfolio Planning (3)

- Given a fixed time limit:
 - Can benefit from splitting this across <u>multiple algorithms</u>!
 - → <u>Portfolio</u> planning





Fast Downward Stone Soup

"We'll cook a soup using only a stone!

But of course it's tastier if you contribute some of this, and you contribute some of that, and..."

FDSS (1)



- Fast Downward Stone Soup (2011): <u>Learning</u>
 - Given test examples from *earlier* domains (2008)
 - Which configurations to use
 - How much time to assign to each config

Algorithm	Score	Time	Marginal	
BJOLP RHW landmarks LM-cut h^1 landmarks M&S-bisim 1 h^{max} M&S-bisim 2 blind M&S-LFPA 10000 M&S-LFPA 50000	605 597 593 588 447 427 426 393 316 299	$\begin{array}{c} 455 \\ 0 \\ 569 \\ 0 \\ 175 \\ 0 \\ 432 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{array}$	$ \begin{array}{c} 46\\ -26\\ -8\\ -20\\\\\\\\\\\\\\\\\\\\ -$	4 of 11 configurations selected for sequential <u>optimal</u> planning
M&S-LFPA 100000	286	0		
Portfolio "Holy Grail"	654 673	1631		

FDSS (3)



- For satisficing planning:
 - Far more algorithms and variations to choose from!
 - Lack of time → tested a subset...

Search	Evaluation	Heuristics	Performance	Time	Marg. Contribution
Greedy best-first	Eager	$h^{ m FF}$	926.13 / 1021	88	1.82/0
Weighted $A^* (w = 3)$	Lazy	$h^{ m FF}$	921.71 / 1023	340	10.02/5
Greedy best-first	Eager	$h^{\rm FF}, h^{\rm CG}$	919.24 / 1023	76	1.15/0
Greedy best-first	Eager	$h^{\text{add}}, h^{\text{FF}}, h^{\text{CG}}$	909.75 / 1021	0	_
Greedy best-first	Eager	$h^{\rm FF}, h^{\rm CG}, h^{\rm cea}$	907.52/1010	73	1.25/0
Greedy best-first	Eager	$h^{\rm FF}, h^{\rm cea}$	906.92/1008	0	_
Greedy best-first	Eager	h ^{add} , h ^{FF} , h ^{CG} , h ^{cea}	903.57 / 1012	0	_
Greedy best-first	Eager	$h^{\mathrm{add}}, h^{\mathrm{FF}}$	900.52/1015	90	1.51/1
Greedy best-first	Eager	$h^{\text{add}}, h^{\text{CG}}, h^{\text{cea}}$	892.08 / 1012	0	
Greedy best-first	Eager	$h^{\text{add}}, h^{\text{FF}}, h^{\text{cea}}$	890.96 / 1002	0	_
Greedy best-first	Eager	h^{CG}, h^{cea}	889.93 / 1009	0	_
Greedy best-first	Eager	$h^{\text{add}}, h^{\text{CG}}$	888.64 / 1014	0	_
Greedy best-first	Lazy	$h^{\rm FF}$	880.12/1042	171	7.24/9
Greedy best-first	Eager	h^{cea}	878.58/ 990	84	3.45/2
Greedy best-first	Eager	$h^{\mathrm{add}}, h^{\mathrm{cea}}$	877.41/ 999	0	_
Greedy best-first	Lazy	$h^{\rm FF}, h^{\rm CG}, h^{\rm cea}$	874.64 / 1035	0	_
Weighted A^* ($w = 3$)	Eager	h^{FF}	874.18/ 920	87	2.75/0
Greedy best-first	Eager	h^{add}	872.74 / 1006	0	_
Greedy best-first	Lazy	$h^{\rm FF}, h^{\rm cea}$	872.48 / 1037	0	_
Greedy best-first	Lazy	$h^{\rm FF}, h^{\rm CG}$	871.77 / 1045	49	1.93/2
Greedy best-first	Lazy	$h^{\text{add}}, h^{\text{FF}}, h^{\text{CG}}, h^{\text{cea}}$	861.06 / 1032	0	_
Greedy best-first	Lazy	$h^{\text{add}}, h^{\text{FF}}, h^{\text{cea}}$	860.64 / 1031	0	_
Greedy best-first	Lazy	$h^{\text{add}}, h^{\text{FF}}, h^{\text{CG}}$	860.04 / 1042	0	_
Greedy best-first	Lazy	$h^{\mathrm{add}}, h^{\mathrm{FF}}$	859.72/1046	0	_
Weighted A^* ($w = 3$)	Lazy	h ^{cea}	849.66 / 1001	0	_
Weighted A^* ($w = 3$)	Eager	h^{cea}	844.67 / 938	0	_
Greedy best-first	Lazy	h^{CG}, h^{cea}	841.78 / 1026	27	1.25/0
Greedy best-first	Lazy	$h^{\mathrm{add}}, h^{\mathrm{cea}}$	839.60/1020	0	_
Greedy best-first	Lazy	$h^{\mathrm{add}}, h^{\mathrm{CG}}, h^{\mathrm{cea}}$	835.33 / 1019	0	_
Greedy best-first	Lazy	$h^{\mathrm{add}}, h^{\mathrm{CG}}$	831.28 / 1030	0	_
Weighted A^* ($w = 3$)	Lazy	hadd	830.39 / 1006	50	0.90/0
Weighted A^* ($w = 3$)	Eager	h^{add}	828.76/ 936	166	3.35/3
Greedy best-first	Lazy	h^{cea}	827.57 / 1014	56	2.04/2
Weighted A^* ($w = 3$)	Eager	h^{CG}	822.46 / 906	89	2.30/1
Greedy best-first	Lazy	h^{add}	808.80/1019	0	_
Greedy best-first	Eager	h^{CG}	802.47 / 920	0	_
Weighted A^* ($w = 3$)	Lazy	h^{CG}	782.14/ 908	73	2.57 / 1
Greedy best-first	Lazy	h^{CG}	755.43/ 924	0	_
Portfolio			1057.57 / 1071	1519	
"Holy Grail"			1078.00/1078		
-					

Search	Evaluation	Heuristics	Performance	Time	Marg. Contribution
Greedy best-first	Eager	$h^{ m FF}$	926.13 / 1021	88	1.82/0
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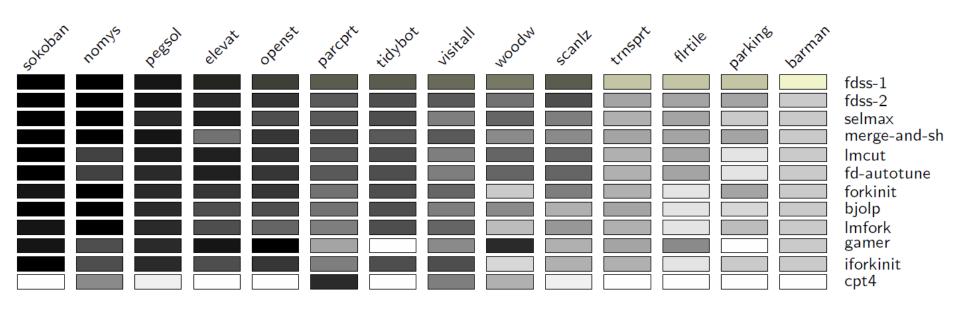
Results: 2011

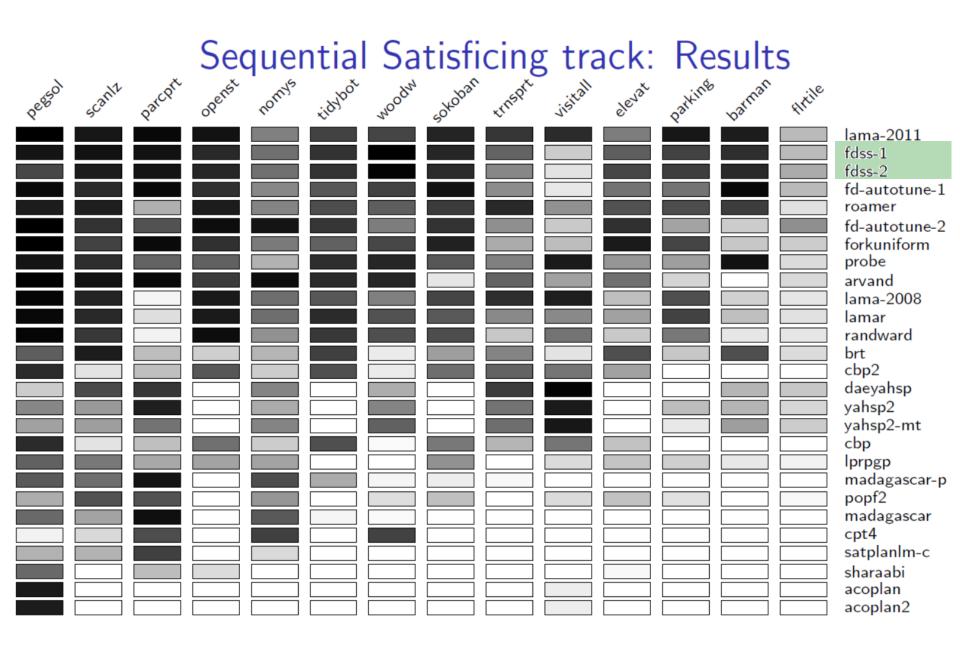
http://www.plg.inf.uc3m.es/ipc2011-deterministic/

IPC 2011: Optimization

- Results from IPC-2011
 - Using new, previously unknown domains

Sequential Optimization track: Results





2014

What you always wanted to know about the deterministic part of the International Planning Competition (IPC) 2014 (but were too afraid to ask)

MAURO VALLATI¹, LUKÁŠ CHRPA^{2,3} and THOMAS L. MCCLUSKEY⁴

Planner	Score	# Solved	% Solved	Borda	Average Borda
IBaCoP2	166.2	198	70.7	205	14.6
IBaCoP	162.7	196	70.0	206	14.7
Mercury	153.0	172	61.4	189	13.5
MIPlan	150.0	168	60.0	192	13.7
Jasper	144.9	173	61.8	201	14.4
FD-Uniform	143.3	172	61.4	196	14.0
FD-Cedalion	137.3	160	57.1	189	13.5
ArvandHerd	137.1	158	56.4	197	14.1
FDSS-2014	127.9	151	53.9	184	13.1
DPMPlan	125.5	147	52.5	158	11.3
USE	107.1	163	58.2	140	10.0
NuCeLaR	101.4	122	43.6	162	11.6
RPT	98.3	127	45.4	144	10.3
BFS(f)	96.1	104	37.1	146	10.4
BiFD	87.0	112	40.0	130	9.3
DAE-YAHSP	64.2	100	35.7	107	7.6
Freelunch	61.2	110	39.3	111	7.9
YAHSP3-MT	58.5	118	42.1	104	7.4
YAHSP3	48.1	92	32.9	95	6.8
Planets	25.0	26	9.3	72	5.1

Table 3International Planning Competition (IPC) score, number of problems solved, success rate, Borda score andaverage Borda score for the *sequential satisficing* track participants

Bold indicates best result, according to the corresponding metrics. Solvers are ordered following IPC score.

Planner	Score	# Solved	% Solved	Borda	Average Borda
Planner IBaCoP2 IBaCoP Mercury MIPlan Jasper FD-Uniform FD-Cedalion ArvandHerd FDSS-2014 DPMPlan USE NuCeLaR RPT BFS(f) BiFD DAE-YAHSP Freelunch YAHSP3-MT	Score 166.2 162.7 153.0 150.0 144.9 143.3 137.3 137.1 127.9 125.5 107.1 101.4 98.3 96.1 87.0 64.2 61.2 58.5	# Solved 198 196 172 168 173 172 160 158 151 147 163 122 127 104 112 100 110 118	No LAMA here? Completely outdated?	Borda Part of many pe including th winners.	ortfolios, e two
YAHSP3 Planets	48.1 25.0	92 26			

Table 3International Planning Competition (IPC) score, number of problems solved, success rate, Borda score andaverage Borda score for the *sequential satisficing* track participants

Bold indicates best result, according to the corresponding metrics. Solvers are ordered following IPC score.

IBaCoP 2014



- IBaCoP: Instance-Based Configured Portfolios
 - #I and #2 in the Sequential Satisficing Track 2014
 - based on:
 - ARVAND (Nakhost, Valenzano, and Xie 2011)
 - FD-AUTOTUNE | & 2 (Fawcett et al. 2011)
 - FD STONE SOUP (FDSS) | & 2 (Helmert et al. 2011)
 - LAMA 2008 & 2011 (Richter, Westphal, and Helmert2011)
 - PROBE (Lipovetzky and Geffner 2011)
 - MADAGASCAR (Rintanen 2011)
 - RANDWARD (Olsen and Bryce 2011)
 - YAHSP2-MT (Vidal 2011)
 - LPG-TD (Gerevini et al. 2004)

2018

https://ipc2018-classical.bitbucket.io/

Results: Satisficing, IPC 2018



										_	
LAPKT- POLYNOMIAL- BFWS	13.30	17.84	11.92	8.82	10.65	5.00	9.62	2.33	8.63	2.10	90.20
IBaCoP-2018	2014:#1-2	5.83	14.66	0	6.40	8.75	0	7.95	8.80	10.33	73.56
IBaCoP2-2018	2017.#1-	5.95	11.53	0	7.18	8.00	0	7.91	7.20	7.23	66.84
MERWIN	10.83	0	10.10	0	5.82	12.0	0	4.94	11.54	7.71	62.93
mercury2014	2014:#3	0	8.67	0	5.82	11.00	0	3.52	12.23	7.69	61.65
LAPKT-DFS+	10.55	12.80	6.72	1.00	5.00	5.00	7.81	4.21	7.79	0	60.89
fs-sim	11.47	5.95	5.16	0	10.47	4.00	0	7.94	4.70	3.90	53.60
fs-blind	3.00	6.00	5.47	0	12.14	4.00	0	7.06	5.32	7.33	50.32
freelunch- doubly-relaxed	7.99	1.57	0.19	0	0	6.00	0	5.57	0.72	0	22.04
freelunch- madagascar	0	2.32	1.96	0	3.00	8.00	0	1.00	0	0	16.27
Symple-2	1.00	2.00	0	0	2.00	5.00	0	0	0	1.00	11.00
Symple-1	1.00	2.00	0	0	2.00	5.00	0	0	0	1.00	11.00
alien	4.24	0	1.12	0	0	4.00	0	0	0	0	9.36

Results: Satisficing, IPC 2018



Score	Agricola	Caldera	Data Network	flashfill	Nurikabe	Organic Synthesis	Settlers	Snake	Spider	Termes	SUM
Fast Downward Stone Soup 2018	Dentfelie	13.97	10.73	13.74	18.43	9.75	16.6	7.20	10.67	8.68	123.27
Fast Downward Remix	Portfolio	14.92	10.58	12.85	18.61	9.00	16.21	7.24	10.78	6.95	120.69
LAPKT-DUAL- BFWS	New str	ategy!	11.79	16.66	14.79	11.75	6.73	9.34	12.12	5.80	119.62
Saarplan	Portfolio	11.76	12.47	13.56	16.64	11.00	9.90	8.36	10.93	7.77	116.87
DecStar	12.42	13.64	9.99	13.74	12.42	9.75	15.68	4.03	12.79	6.75	111.21
Cerberus	10.62	10.92	11.71	9.74	15.50	12.0	9.87	5.72	13.94	7.94	107.95
Baseline: LAMA 2011	9.53 ^{9.53}	13.90	7.48	13.74	10.59	12.0	15.76	3.55	13.42	7.58	107.56
LAPKT-BFWS- Preference	10.99	15.94	8.18	11.74	12.63	7.00	8.43	15.78	10.29	5.46	106.44
Cerberus-gl	10.62	10.92	11.71	9.74	15.50	12.0	9.11	5.72	14.16	6.64	106.13
OLCFF	13.74	11.76	12.19	0.82	17.92	9.00	0	7.62	11.24	7.79	92.09
LAPKT- POLYNOMIAL- BFWS	13.30	17.84	11.92	8.82	10.65	5.00	9.62	2.33	8.63	2.10	90.20

Fast Downward Stone Soup 2018

- FDSS update 2018:
 - I44 Fast Downward configurations to choose from
 - Trained using problems from IPC 1998-2014 + other sources
 - Result:
 - Portfolio uses 41 configurations, between 8 and 135 seconds
 - Overall score 1999.93, compared to best component 1650.40 (running on non-training problems