Compiling PDDL3 Qualitative Preferences without Using Automata

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Abstract

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Introduction

Related Work

Propositional Planning with Qualitative PDDL3 Preferences

Operator-Preference Interactions

Compilation of Qualitative Preferences

Experimental Results

Experiments Description

We implemented the proposed compilation scheme and have evaluated it by two sets of experiments with different purposes. On the one hand we evaluated the scheme in a satisficing planning context in which we focused on the search for sub-optimal plans, while in the other we focuse on the search of optmial plans.

Regarding the comparison in the context of the satisficing planning we have considered the following strips+ planning system LAMA(**?**), Mercury (**?**), MIPlan (**?**), IBaCoP2 (**?**), which are some of the best performing planning system in IPC8 (**?**), and Fast Downward Stone Soup 2018(**?**), Fast Downward Remix(**?**) (abbreviated with FD-Remix), which are some of the best performing planning system in the last IPC9 (**?**) which have been compared with LPRPG-P (**?**), which is one of the performing planner which supports PDDL3 preferences.

As benchmark we have considered the five domains of the qualitative preference track of IPC5 (**?**) which involve always, sometime, sometime-before, at-most-once and soft goal preferences, i.e Rovers, TPP, Trucks, Openstacks and Storage.

For each original problem all preferences and each original utility were kept. The the classical planners were runned on the compiled problems while LPRPG-P was runned on the original problems of the competition. All the experiments were conducted on a 2.00GHz Core Intel(R) Xeon(R) CPU E5-2620 machine with CPU-time and memory limits of 30 minutes and 8GiB, respectively, for each run of every tested planner. The time for the preferences goal compilation was included in the 30 minutes.

Table 1 shows the performances of the considered planning system in term of plans quality. As quality measure we used IPC quality score, a popular metric which is described in (**?**) of which we have reported a brief description.

Given a planner p and a task i we assign, if p solves i, the following qualitative score to p:

$$\mathit{score}(p,i) = \mathit{cost}_{\mathit{best}}(i)/\mathit{cost}(p,i)$$

where $\mathit{cost}_{\mathit{best}}(i)$ is the cost of the best know solution for the task i found by any planner, and $\mathit{cost}(p,i)$ is the cost of the solution found by planner p in 30 minutes. In our case our reference for $\mathit{cost}_{\mathit{best}}(i)$ is equal to the cost of the best solution among the tested planners within 30 minutes. If p did not find a solution within the time assigned, then $\mathit{score}(p,i)$ is equal to 0 in order to reward both quality and coverage.

The quality score assigned to each tested planner p is set equal to sum of the quality scores assigned to p over all the considered test problems:

$$\mathit{score}(p) = \sum_{i \in \mathit{tasks}} \mathit{score}(p,i)$$

Table 1 reports the quality comparison using the IPC score described above. It is splitted into six parts, at top we have reported the qualitative comparision considering all kinds of preferences together in the benchmark, while in the remaining subtables we have splitted the calculation of IPC quality score considering each kind of preference seperately. In the the header of each subtable we have reported the class of considered preferences.

NOTA (FP): selezionare un numero di pianifiacatori significativi da includere nella tabella per alleggerire la tabella.

Figures 1—**??** show the qualitative comparison in a more detailed way. In these histograms we have reported, for each istance of each domain, another quality measure, which we have denoted with α_{cost}. In particular we have evaluated the best performing planners according to the results showed in Table 1 which are LAMA, IBaCoP2 and LPRPG-P respectively. Each figure is associated with one of the considered domains.

We reported a brief description of the metric α_{cost} that we used. Given a planner p and a task i we assign, if p solves i, the following score to p:

$$\alpha_{cost}(p,i) = cost(p,i)/cost_{total}(i) = \frac{\sum_{P \in \mathscr{P}(i)\,:\,\pi \not\models P} c(P)}{\sum_{P \in \mathscr{P}(i)} c(P)}$$

where $cost(p,i)$ is the cost of the solution found by planner p for the task i within 30 minutes and $cost_{total}(i)$ is the sum of the costs of all the preferences involved in the task i (note that $\mathscr{P}(i)$ denote the set of the preferences of the task i).

From the previous definition, $\alpha_{cost}(p,i)$ could vary between 0 and 1. If $\alpha_{cost}(p,i) = 0$, then it means that the numerator $cost(p,i)$ is equal to 0 and that p has found an optimal plan for i which satisfies all the preferences of the problem. On the contrary, if $\alpha_{cost}(p,i) = 1$, then it means that p has found the worst plan for i where all the preferences of the problem are violated.

More generally given an instance i, the ratio $\alpha_{cost}(p,i)$, comparing plans produced by different systems, tell us which planner has achieved the satisfaction of the most useful subset of preferences in absolute terms. In particular, the planner with the lowest ratio is the planner who got the best performance on that particular instance.

Satisficing Planning Results

In Table 1, considering all kinds of preferences, we can observe that all the classical planning system, except for MIPlan and Mercury, perform overall better than LPRPG-P in term of IPC score while MIPlan and Mercury performs overall worse. The compilative approach seems at glance to be preferable in Rovers, Trucks and Storage. In these domains each classical planner performs better or at least comparable than LPRPG-P (except for Mercury in Trucks); IBaCoP2 performs particularly well in Rovers while LAMA in Trucks. Also MIPlan get a well performance in Trucks but is penalized due to coverage (it solves only 15 instances out of 20).

NOTA (FP): commento TPP - punto di debolezza.

In TPP the compilative approach seems to be very ineffective, each classical planner achieves an extremely lower quality performance compared to LPRPG-P. The bad performances in this domain are probably due to the many soft goals because, as shown in (**?**) (articolo pruning+softgoal), the compilation of soft goals can be sometime problematic. Indeed the part of Table 1, which concerns soft goals, cleary shows that LPRPG-P is overall more performing than the classical planners especially in TPP in term of satisfied soft goal.

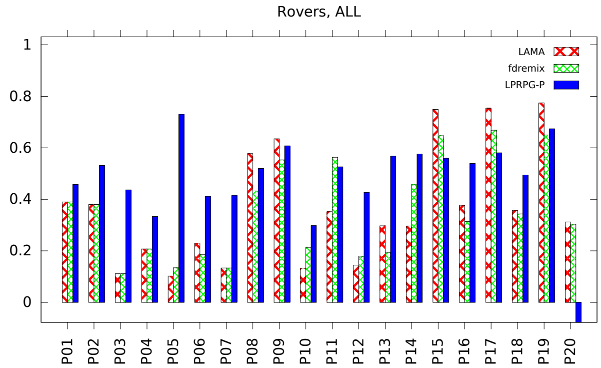
Regarding Opentacks the tested planners achieve a comparable performance even if the classical planners are slightly penalized compared to LPRPG-P. Also in this case the classical planners have difficulty to satisfy soft goal as shown in Table 1.

Looking at Figure 1a we can observe that LAMA and FD-Remix generally compute higher quality plans than LPRPG-P in Rovers, in particular they find better plan in 15 and 16 instances out of 20 respectively. Looking at Figure 1b we can observe that LAMA and FD-Remix compute lower quality plans that LPRPG-P for more than half of the instances. Both classical system work better than LPRPGP in smaller instances but they get worse as the size increases. Looking at Figure 1c we can say that LAMA and FD-Remix performs better for more than half of the instances, in particular they find better plan in 13 and 16 instances out of 20. Note that the classical planners get the optimal solution for some of the first seven instances. Looking at Figure 1d we can say that both approaches achieve a comparable performance even if LPRPG-P generally finds slightly better solutions than both classical competitors in 13 instances out of 20.

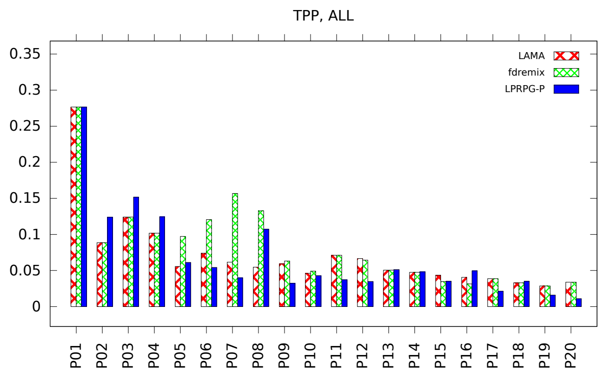
NOTA (FP): scrivi commento Storage.

$\mathscr{P}$						
Planner	Rovers	TPP	Trucks	Openstacks	Storage	TOTAL
LAMA	17.37	8.61	15.57	19.26	18.34	79.14
FD-Remix	17.24	7.1	17.76	18.96	16.26	77.32
FDSS 2018	16.95	7.03	17.16	18.66	17.19	76.99
IBaCoP2	18.9	9.68	10.0	17.82	15.78	72.19
LPRPG-P	10.81	18.74	7.07	19.68	12.95	69.25
MIPlan	16.9	8.8	9.23	17.32	14.47	66.72
Mercury	15.61	8.57	7.82	18.02	14.56	62.59
$\mathcal{A}$						
Planner	Rovers	TPP	Trucks	Openstacks	Storage	TOTAL
LAMA	15.09	20.0	15.0	20.0	20.0	90.09
IBaCoP2	16.19	20.0	13.0	19.0	19.0	87.19
FDSS 2018	14.19	17.0	18.0	17.83	20.0	87.02
MIPlan	14.71	20.0	12.0	19.0	20.0	85.71
FD-Remix	12.64	15.0	15.0	18.5	19.0	80.14
Mercury	13.8	20.0	4.0	20.0	20.0	77.8
LPRPG-P	14.46	7.0	0.0	19.5	11.0	51.96
$\mathcal{SG}$						
Planner	Rovers	TPP	Trucks	Openstacks	Storage	TOTAL
LPRPG-P	—	19.45	16.48	19.39	15.02	70.34
FD-Remix	—	14.73	17.12	18.59	18.63	69.07
FDSS 2018	—	14.66	16.49	18.36	18.49	68.01
LAMA	—	14.41	14.52	18.68	19.05	66.66
IBaCoP2	—	16.03	10.7	17.19	18.67	62.59
MIPlan	—	15.08	9.85	16.67	19.38	60.97
Mercury	—	14.83	7.78	17.36	18.35	58.32
$\mathcal{AO}$						
Planner	Rovers	TPP	Trucks	Openstacks	Storage	TOTAL
Mercury	16.3	20.0	19.0	—	20.0	75.3
FDSS 2018	16.1	17.0	20.0	—	19.0	72.1
FD-Remix	16.07	16.0	20.0	—	18.0	70.07
LAMA	15.35	15.0	19.0	—	20.0	69.35
MIPlan	13.3	16.0	15.0	—	20.0	64.3
IBaCoP2	12.9	15.0	16.0	—	19.0	62.9
LPRPG-P	13.0	1.0	19.0	—	12.0	45.0
$\mathcal{SB}$						
Planner	Rovers	TPP	Trucks	Openstacks	Storage	TOTAL
LAMA	18.09	20.0	18.0	—	19.0	75.09
Mercury	16.35	20.0	14.5	—	20.0	70.85
MIPlan	18.53	20.0	12.0	—	20.0	68.53
FD-Remix	15.83	16.0	18.5	—	20.0	68.33
FDSS 2018	15.8	17.0	18.5	—	19.0	68.3
IBaCoP2	18.01	20.0	12.0	—	18.0	68.01
LPRPG-P	7.41	14.0	15.5	—	7.0	43.91
$\mathcal{ST}$						
Planner	Rovers	TPP	Trucks	Openstacks	Storage	TOTAL
	15.76	11.0	—	—	20.0	46.76
FDSS 2018	16.15	8.0	—	—	20.0	44.15
IBaCoP2	16.78	10.0	—	—	17.0	43.78
LPRPG-P	9.53	17.0	—	—	15.0	41.53
FD-Remix	15.42	8.0	—	—	17.0	40.42
MIPlan	14.88	9.0	—	—	15.0	38.88
Mercury	12.76	4.0	—	—	13.0	29.76

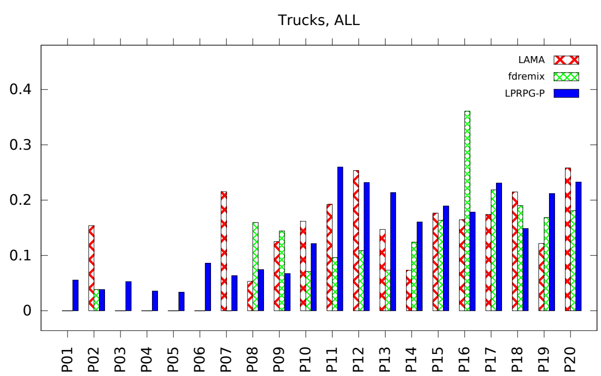
Table 1: Temp caption



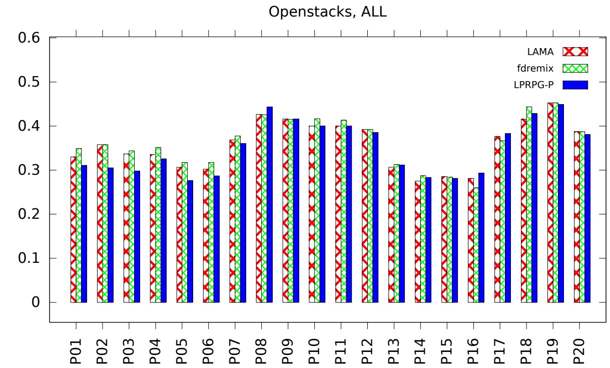
(a) Rovers



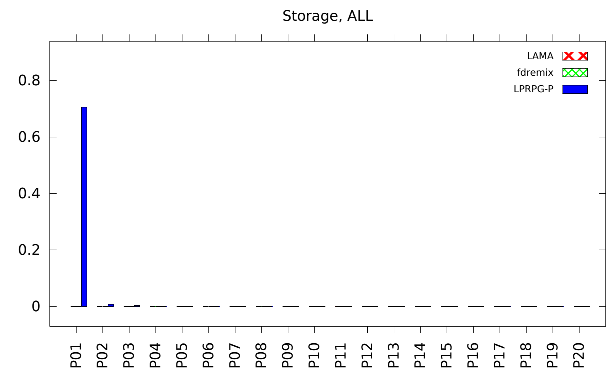
(b) TPP



(c) Trucks



(d) Openstacks



(e) Storage

Figure 1: Quality Comparison using α_{cost} for each domain. Each bar represents the α_{cost} of the best plan produced by the considered planner. The negative bar represents an instance which has not been solved or that has no preferences of that kind. From the top to bottom we have provided the results about α_{cost} calculated considering each kind of preferences for Rovers, TPP, Trucks, Openstacks and Storage.

Optimal Planning Results

Similarly to what to what has been done in **??** (articolo NEBEL), we have tested our scheme using some admissible heuristics which are h^{blind}, h^{max} an $h^{\text{M\&S}}$ which guarantee us the optimality of the solution found. Starting from the IPC5 domains, we generated simpler instances by randomly sampling subsets of the soft trajectory constraints. Starting from each instance we have generated five new instances with 1%, 5%, 10%, 20% and 40% of the (grounded) soft trajectory constraints while the hard goals have remained unchanged.

Since we do not have the instances that have been used in the aforementioned paper, we have generated, for each percentage of sampling preferences (excpet for 100 %), five sampled instances in order to average the obtained results. The results about this experiment are shown Table 2. The results inherent to Openstacks have been excluded because it was not possible to find optimal plans even for the simplest instances.

Conclusions

Domain	h^{blind}	h^{max}	$h^{\text{m\&s}}$
Storage	49.0	41.0	23.0
Rovers	23.0	23.0	23.0
TPP-p	36.0	33.0	35.0
Trucks	23.0	28.0	23.0
TOTAL	33.0	31.0	26.0

Table 2: Coverage of our compilation scheme on the IPC5 benchmarks set with additional instances with random sampled soft-trajectory constraints, A* search for optimal solution.