Towards domain-independent biases for action selection in robotic task-planning under uncertainty

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Keywords: Action selection, Monte-Carlo Planning, Planning under uncertainty

Abstract: Task-planning algorithms for robots must quickly select actions with high reward prospects despite the huge variability of their domains, and accounting for the high cost of performing the wrong action in the "real-world". In response we propose an action selection method based on reward-shaping, for planning in (PO)MDP's, that adds an informed action-selection bias but depends almost exclusively on a clear specification of the goal. Combined with a derived rollout policy for MCTS planners, we show promising results in relatively large domains of interest to robotics.

1 Introduction

Planning under uncertainty requires computing values for states and actions, that reflect a combination of some form of utility or reward and their probability. These planning problems are often modelled as Markov Decision Processes (MDP's) or Partially Observable MDP's (POMDP's), and solved using many well known methods among which Monte-Carlo Tree Search (MCTS) is a popular choice, especially in the online planning community. The modern standard for MCTS is UCT (Kocsis and Szepesvári, 2006), which uses the UCB1 formula (Auer et al., 2002) in search trees, thus guaranteeing asymptotic convergence and solutions that minimize regret. Recently POMCP (Silver and Veness, 2010), an extension of UCT for partially observable domains, has become somewhat of a reference point for POMDP planning and contributed to the consolidation of Monte-Carlo algorithms as a more efficient alternative to traditional POMDP solvers.

Despite these advances, transferring these methods to online planning in robots and other similar agents is not easy. The onboard hardware of robots imposes severe limitations on computational resources, and the high variability and uncertainty of domains of interest still render most of these algorithms inadequate for fast, online planning. Planning in the "real-world" introduces additional considerations that are often overlooked in maze problems and other game-like domains: not only is their state-complexity different, but there is also a certain amount of consistency and regularity that may be exploited.

We argue that several simplifications and assumptions are not only possible, but necessary, in order to achieve satisficing behavior in such domains. One such simplification is quickly focusing on promising states, and avoiding less promising ones. We have developed these ideas while trying to provide a formal interpretation of the intuitive concept of "relevance", which in planning terms may be seen as a reliable (albeit imperfect) attentional filter guiding action selection, which may offer an intuitive way of handling problems with high dimensionality. Planning algorithms should be able to quickly identify promising (high expected value) states and focus on getting there. State values represent a weighted average of future rewards, so the problem reduces to quickly locating these sources of future rewards. One relatively simple idea is preferring actions that lead to subgoals (subsets of some terminal state) while avoiding those that don't, and encouraging these actions by providing additional, positive rewards. Achieving a subgoal objectively brings the agent a step closer to achieving a larger goal, and so we use this idea to formalize a metric of state to goal proximity.

In this paper we propose *partial goal satisfaction* as a way to compute the proximity of states to goals and provide a reward bonus in action selection, which easily becomes an action selection policy for Monte-Carlo rollouts. This is by no means a complete solution to online planning onboard robots, but rather a contribution towards the improvement of action selection in planning algorithms, when information about the goal is available. The intended effect is planning more efficiently in domains with many states and actions.

Alternative, well-known approaches for addressing large planning spaces include value approximation and state aggregation, but these work under the assumption that there are large groups of states that can be clustered together (due to similarity or other reasons) using fixed criteria. At the moment we are interested in how agents may use knowledge of their goal(s) to improve their action selection criteria, in particular by focusing on only a few good alternatives when many options are available, as is the case of domains with high variability and large branching factor.

In the following sections we discuss previous related work, and proceed to explain our proposal. We provide two case studies and an analysis of experimental results, as well as conclusions and future work.

2 Notation

Unless otherwise specified, S and A are finite sets of states and actions respectively and $T(s,a,s')$ is the probability of reaching state s' when executing a in s, which yields a real-valued reward $R(s,a,s')$. An MDP is the tuple $\langle S,A,T,R\rangle$, with discount factor γ. Under partial observability, an agent receives an observation $\omega \in \Omega$ with probability $O(s,a,\omega) = p(\omega|s,a)$ and maintains an internal belief state $b \in B$, where $b(s)$ is the probability of s being the current state. A POMDP is therefore $\langle S,A,T,R,\Omega,O\rangle$. The sequence $h_t = (a_0,\omega_1,\ldots,a_{t-1},\omega_t)$ is the *history* at time t.

The common notation for planning in POMDP's uses belief states, or probability distributions over the entire state space. That is, policies are given in terms of beliefs. In this paper, however, we present our action selection bias in terms of fully observable states and states with mixed observability (states that contain both fully and partially observable features). Our experimental setup uses states sampled from a belief state approximator. Future work includes extending these definitions to more general cases, such as belief states.

3 Related work

Our work centers on improving the performance of action selection for (PO)MDP planning algorithms, relying mostly on UCT (Kocsis and Szepesvári, 2006) and its POMDP extension, POMCP (Silver and Veness, 2010). Unlike more traditional POMDP algorithms that approximate the belief space using vector sets, POMCP uses Monte-Carlo Tree Search (MCTS) and approximates the current belief state using an unweighted particle filter. Because this is a key improvement of the Monte-Carlo family of algorithms, this paper focuses on states with partially observable elements instead of belief states. The concept of mixed observability has produced positive results even outside of MCTS algorithms (Ong et al., 2010). Alternatively, MCTS algorithms have also been used for belief selection in POMDP's (Somani et al., 2013).

Existing approaches addressing the state-space complexity involve clustering states and generalizing state or belief values (Pineau et al., 2003), (Pineau et al., 2006), function approximation (Sutton and Barto, 2012) and random forest model learning (Hester and Stone, 2013). Our main critique of these methods for online task planning is that they have fixed aggregation criteria that do not respond to the connection between states and goals. For instance, states could be clustered together depending on context so their shared values reflect the agent's current goals.

Other approaches generate abstractions for planning and learning over hierarchies of actions (Sutton et al., 1999), (Dietterich, 2000). The drawback is that relatively detailed, prior knowledge of the domain is required to manually create these hierarchies, although recent work suggests a possible way to build them automatically (Konidaris, 2016).

Planning algorithms for (PO)MDP's overlap with reinforcement learning (RL) methods, with the difference that in RL the agent must find an optimal policy while discovering and learning the transition dynamics. Reward shaping is commonly used in RL to improve performance by simply giving additional rewards for certain preferred actions. This generates an MDP with a different reward distribution and therefore different convergence properties, but potential-based reward shaping (PBRS) has been shown to preserve policy optimality (Ng et al., 1999). A study of PBRS in the context of online POMDP planning can be found in (Eck et al., 2016).

Building on these arguments, the work presented in this paper reflects our efforts to provide a general-purpose, PBRS bias for action selection in planning tasks of interest to robotics, in order to address the complexity of planning in domains with large variability, where states or beliefs may not always be easily aggregated.

4 Measuring goal proximity

The main challenge for efficient planning is quickly separating *good* or promising states from *bad* or unwanted states. Even domains without clearly specified goals (eg. pure RL tasks) have terminal states or conditions that establish what must be accomplished and what subgoals the agent should pursue. In robotics, it is reasonable to assume planning agents are somewhat informed and aware of at least part of their goal(s). If no goals are known, the robot should find one. Any sufficiently detailed state description (eg. features needed for planning) provides information to compute, for any given state, some numerical score representing how many features in the terminal state have already been accomplished. The larger this number is, the closer this state is to being a terminal or a goal state. We call this idea partial goal satisfaction (PGS), formalized in equation 1.

PGS is simple to implement in fully observable domains, but due to the uncertainty of observations, estimating this number might be challenging in partially observable domains. Fully observable features can be easily counted in meaningful ways (eq. 2). For partially observable features, information gathering actions should increase the probability that their current, estimated value is correct, thus also affecting the probability of an agent being in some given state ($b(s)$). In other words, collecting information about a given set of partially-observable features yields a better estimate of the world's current, true state. The simplest, most general approach is therefore measuring some form of uncertainty or entropy and providing rewards as this uncertainty is reduced (eq. 3). Let $s \in S$ be a state, decomposed into countable discrete features s_i, G_+ be the set containing the observable features present in the goal, G_- the set of observable restrictions, $\Delta(s)$ the set of states reachable from s (similar to the transitive closure of $T(s,\cdot)$) and G_p the set of partially or non-observable elements, then:

$$\mathrm{pgs}(s) = \sum_{s_i \notin G_p} v(s_i) + \sum_{s_j \in G_p} w(s_j) \tag{1}$$

where:

$$v(s_i) = \begin{cases} 1 & \text{iff } s_i \in G_+ \\ x \in (0,1) & \text{iff } \exists s' \in \Delta(s) \text{ s.t.:} \\ & s'_k \in s' \wedge s'_k \in G_+ \\ 0 & \text{iff } s_i \notin \{G_+ \cap G_-\} \\ -1 & \text{iff } s_i \in G_- \end{cases} \tag{2}$$

and

$$w(s_j) = \begin{cases} 0 & \text{iff } H(s_j) \leqslant T_H \\ -1 & \text{otherwise} \end{cases} \tag{3}$$

This means the different features in each state are evaluated depending on whether they are partially observable ($s_j \in G_p$) or not. Positive, observable features add points and negative features deduct points. State changes that lead to a positive feature ($s'_k \in G_+$) in a future state ($s' \in \Delta(s)$) yield a fraction of a point and help implicitly define subgoals (eg. interacting with an object referenced in the goal, such as picking up the coffee cup that goes on the table), and if no relevant features are present no points are awarded or taken. Partially observable features are scored based on their entropy, punishing features or states with high entropy. Whenever enough information is gathered and the entropy is reduced below some threshold T_H, this punishment is removed. This encourages the agent to quickly get rid of this penalty by executing a number of information gathering actions, which in turn may lead to discovering new reward sources (eg. interacting with relevant but previously unrecognized elements). In principle any combination of the individual elements in the goal may be considered a subgoal for scoring purposes, and only completing all of them simultaneously yields the total, problem-defined terminal reward.

PGS may be useful in different contexts, but it is intended as an optimistic value initialization method that allows an agent to exploit nearby opportunities if available. Directly applying PGS on some planning problems that appear relatively simple, such as some particular blocks world configurations, may not yield the desired results. As explained below, PGS is intended to be used within the context of Monte-Carlo or similar search algorithms, where the optimistic assumptions of PGS will eventually be corrected (if they're wrong) and the problem solved properly.

4.1 PGS in reward shaping

Reward shaping, commonly used to improve the performance of (PO)MDP algorithms and RL problems, works by adding a small, additional reward to some state transitions. These additional rewards often come from an in-depth analysis of the structure of the problem and provide some form of heuristic bias in action selection. The new reward structure defines a decision process with additional reward sources, implicitly introducing subgoals the agent may achieve in order to get closer to the final goal. In our case, instead of providing explicit, domain dependent knowledge to shape rewards, we use the PGS function to encourage the agent to pursue courses of action leading to the completion of subgoals.

Reward shaping substitutes the usual reward function in an MDP with:

$$R(s,a,s') + F(s,a,s') \tag{4}$$

where R is the problem-defined reward distribution and F is a reward bonus. If F has the form

$$F(s,a,s') = \gamma\phi(s') - \phi(s) \tag{5}$$

then it is a potential function and eq. 4 is potential-based. We now define $\phi(s)$ for PGS as

$$\phi(s) = \alpha \mathrm{pgs}(s) \tag{6}$$

where α a scaling factor. Because most (PO)MDP algorithms already use γ to refer to the discount factor, from now on we will refer to γ_{PGS} when in the context of PBRS. In practice, transitions to states that are *closer* to a subgoal (positive reward source) will produce a positive difference, transitions to states that are farther from subgoals generate a negative difference, and other transitions cancel each other out. Normally reward shaping functions are highly domain-dependent and specific for particular problems. PGS manages to attain simplicity and generality, possibly requiring only minor details for implementation, but with values coming from knowledge about goals always available to the agent or robot.

4.2 PGS as a rollout policy

The MCTS family of MDP and POMDP algorithms works by sampling sequences of states from a probabilistic transition model. A tree of states (or in the case of POMCP a tree of histories) is progressively expanded and the average returns and visit counts are maintained per tree node. When enough statistics are available (eg. all known successors of a state have been visited) the UCB1 rule is used to select an action. When a new state is discovered, a rollout or random simulation is performed and its outcome used as an initial value estimation. Rollout policies are therefore largely responsible for the performance of MCTS online planning algorithms. Using PGS as a rollout policy, the agent quickly focuses on actions that directly contribute to the completion of (sub)goals and, likewise, avoids undesirable actions. Selecting actions that maximize state-to-goal proximity can implicitly summarize a very rich array of knowledge and heuristics, that must otherwise be given explicitly. To the best of our knowledge, the effect of evaluating goal proximity within the context of Monte-Carlo rollouts hasn't yet been systematically studied.

Using PGS as a rollout policy (eq. 7) is very simple: given a state s and available actions $a \in A$, select the state $s' \leftarrow (s,a)$ that satisfies the largest amount of subgoals. Ties are broken randomly.

$$\mathcal{A}(s) = \arg\max_{a} \mathrm{pgs}(s' \leftarrow (s,a)) \tag{7}$$

Because PGS is computed as a difference between the current and previous states (eq. 5), when $\gamma_{\mathrm{PGS}} = 1$ only newly completed subgoals produce positive values. For example imagine a robot tasked with collecting and delivering a cup of coffee: during planning, standing next to the cup offers the possibility of picking it up, satisfying a subgoal that yields a reward bonus, therefore becoming the preferred action of the rollout policy. Once holding it, dropping the cup in any place other than the correct location reverts this condition and produces a negative reward, meaning it will never be chosen in a rollout (albeit eventually during simulation, if all actions are systematically sampled). MCTS recommends an action only after arbitrarily many simulations have been carried out, but starting out with the (seemingly) right action greatly improves performance. Unlike with PGS, improved rollout policies often consist of manually designed heuristics and explicit preferred actions.

5 Results

We tested PGS in two well-known and commonly used benchmark problems: the taxi domain, which defines a fully observable MDP and *Rocksample*, a POMDP that scales to very large state spaces. For the former we implemented our own version of UCT, and for the latter we modified the POMCP source code. All tests ran on a desktop workstation with an Intel i7-4790 CPU, 20 GB RAM and Debian GNU/Linux.

The challenge for robot planning under uncertainty is achieving good performance within a finite horizon, fast enough, even in large problems. These two scenarios show the performance of PGS using limited resources (very few Monte-Carlo simulations) and how it scales in considerably large versions of Rocksample.

5.1 Taxi domain

The taxi domain, first proposed in (Dietterich, 2000), is a simple, fully-observable MDP often used to test planning and learning algorithms. The taxi agent moves in any of four directions in a 5×5 grid and must pick up a passenger located in one of four possible depots, and bring it to another depot. A slight variation is the "fickle taxi" in which movement is non-deterministic: with a small probability (eg. $p = 0.1$) the taxi will end up East or West of its intended direction. Possible actions are moving North, East, South or West, collecting a passenger when standing on the same grid cell or dropping the passenger (when carrying one). Rewards are -1 for each regular move, -10 for dropping the passenger in the wrong location and 20 for delivering a passenger correctly, which also terminates the episode. We chose one instance of the taxi domain and obtained the total discounted reward of its optimal policy, 8.652, in order to compare it with the experimental results. This particular configuration and in general the taxi domain are illustrated in figure 1, where the dark cell at the top left corner is the goal depot where the passenger must be dropped. The walls shown in the picture are also included in the experiment which means the agent's movement is restricted, in cells next to walls, to only open, adjacent cells.

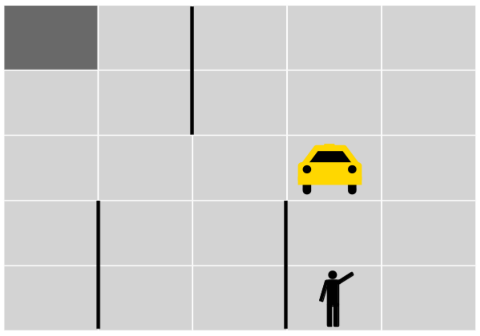


Figure 1: The taxi domain

PGS in the taxi domain is easy to formalize as all elements are fully observable. We simply award 0.25 points for picking up the right passenger and 1 point for dropping it at the correct depot (G_+). There are no restrictions ($G_- = \emptyset$). The terminal state reward is preserved but the rest rely on PGS, using $\gamma_{\text{PGS}} = 1$ and $\alpha = 10$ to reflect the punishment for illegally dropping a passenger. Finally, a discount factor of $\gamma = 0.95$ and search depth of 90 steps were used within UCT. It is common to allow the taxi to start only over a depot, but in our experiments it could be anywhere on the grid. We ran UCT with PGS rewards and PGS rollout policy in both (regular and fickle) versions of the taxi domain, and obtained the average discounted rewards and running times over 1000 runs. Table 1 shows the result of repeated runs on the fixed task (fig. 1) and a set of randomly generated episodes (randomized origin and destination depots, and taxi starting location) using 1024 simulations.

Results are especially promising when we consider the total discounted reward of the optimal policy

Transition	Episodes	Avg. Return	Time
Normal	Fixed	6.161	3.049
	Random	4.257	3.531
Fickle	Fixed	3.275	4.410
	Random	2.138	4.176

Table 1: Performance in the taxi domain after 1000 runs with 1024 simulations

in the fixed (non fickle) task (8.652). Restricting the amount of computation to only 256 simulations per move (≈ 1.6 s. per episode), the PGS-based planner achieved an average discounted reward of 5.089. On random tasks it is important to mention that episodes were terminated after 5 s., but their (negative) reward still averaged.

Averaging performance, especially with stochastic methods, hides some additional, interesting details of particularly good runs. We ran a separate batch of 1000 episodes using 1024 simulations, of which 616 finished in 2 s. or less and 797 in 3 s. or less. In these runs the mean discounted reward was particularly high and the statistical mode was, also for the entire set, the optimal discounted reward (8.652). Results are shown in table 2.

Time (s.)	Count	Mean	Min	Mode
$\leqslant 2$	616	7.499	3.523	8.652
$\leqslant 3$	797	7.125	1.97	8.652

Table 2: Discounted rewards with 1024 simulations and limited runtime

Interestingly, it seems that when given more time (or simulations), a larger number of unsuccessful runs appear (therefore reducing the minimum and average returns). This could be due to the fact that, being somewhat greedy, UCT can sometimes enter loops when attempting to solve simple discrete mazes. At a certain distance (sufficiently far from a reward source) all possible next states (eg. cells in the maze) appear equally good (or bad) at first and their action values might be very similar or even the same. Given more time, this type of repetitive behavior results in very long policies with extremely low returns. With *enough* planning time (convergence in RL and MCTS methods is, after all, guaranteed after asymptotically many iterations), the agent might be able to break out of this loop, locate the goal and improve its policy. This is precisely the reason for introducing additional reward sources, but we are interested in finding reasonably good solutions as quick as possible. The taxi domain is an interesting benchmark because, despite being extremely simplified in terms of tasks and actions, there are many "empty" cells that create large groups of very similar states. In richer domains with more features, where naive planning algorithms may require systematic deliberation and long run-times, PGS shows very promising results (eg. Rock-sample in next subsection).

Our main motivation for speeding up MDP planning is transferring these methods to robotic task planning, so we are particularly interested in maintaining good levels of performance and not necessarily optimizing indefinitely. This means, in practice, we are aiming at solving (parts of) complex domains within a few seconds and not necessarily milliseconds. Despite being essentially a *toy* problem because of its size and full observability, the taxi domain is a abstraction of a common manipulation task (navigating, collecting, delivering) and our results show PGS succeeds in achieving good levels of performance with very limited time, planning directly on an unfactored MDP.

5.2 Rocksample

Rocksample, originally found in (Smith and Simmons, 2004), is a commonly used problem that simulates a Mars rover tasked with collecting valuable rocks. This problem corresponds to a POMDP in which the location of the agent and the rocks are known, but the value of these rocks is initially unknown and must be determined by the use of a noisy sensor that returns one of two observations, *good* or *bad*, with a given reliability. *Rocksample*$[n,k]$ defines an $n \times n$ grid with k rocks, where the agent may move in any of four directions, sample a rock if standing directly on top of it, or use the sensor on any rock (action $check_i$ for rock i) for a total of $5+k$ actions (see fig. 2). Rewards are 10 for sampling good rocks, -10 for sampling bad rocks, 10 for exiting (East) and -100 for leaving the grid in any other direction (Smith and Simmons, 2004). We used POMCP as a POMDP solver (Silver and Veness, 2010), but modified it to test our proposal.

POMCP is a particularly fast POMDP solver mainly due to two reasons: it uses an unweighted particle filter to approximate the belief state, avoiding costly belief updates, and it expands a tree of histories instead of states, circumventing the curse of dimensionality. Within POMCP, instead of a belief state the agent receives a state sampled from the particle filter, which corresponds to a state with mixed observability. This way we were able to test our methodology within a POMDP solver, albeit relying on states that contain partially observable features (thus, not directly introducing preference over beliefs). In addition, POMCP uses slightly enhanced rocksample states, where the probability that a rock is good is updated directly after every corresponding *check* action, using the sensor efficiency and the previous likelihood. We defined $C = G_+ \cap G_-$ to be the set of collected rocks, and G_p the remaining rocks. Scoring function $v(s_i)$ returns 1 for good rocks with good observations (G_+) and -1 for bad rocks (G_-). Function $w(s_j)$ returns -1 if $H_b(p_r) > 0.5$, that is, if the binary entropy of rock r (s_j) is higher than 0.5. POMCP comes with a preferred actions policy, which uses manually encoded heuristics such as "head North if there are rocks with more positive observations" or "check rocks that have been measured less than five times and have less than two positive observations". Clearly, PGS succeeds in avoiding this level of over specification.

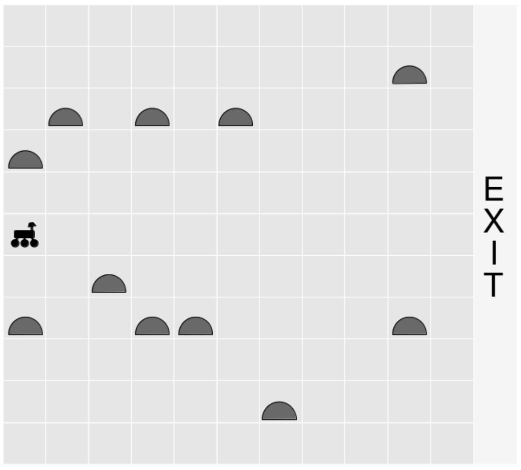
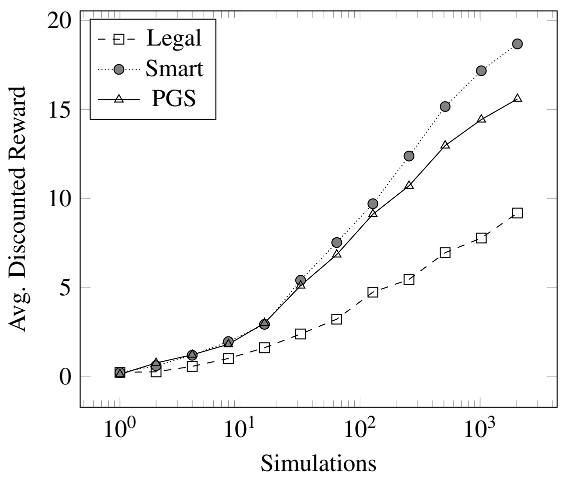


Figure 2: Special layout for Rocksample$[11,11]$

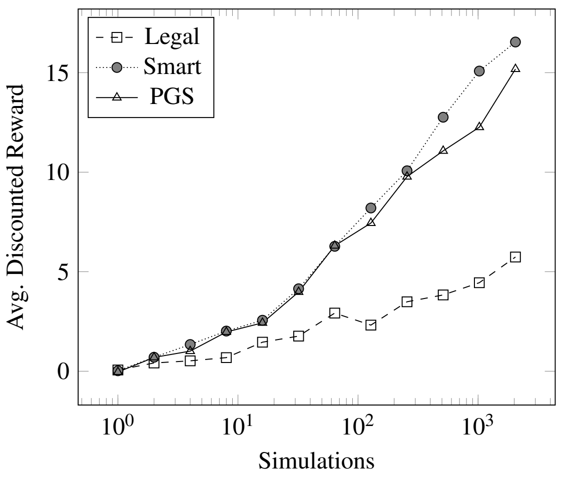
We used $\gamma_{\text{PGS}} = 1$ and $\alpha = 10$ (to reflect the difference in rewards received when sampling good and bad rocks). This scoring function deducts points for undesirable states (eg. collecting bad rocks, high entropy for any rock) and only adds points when collecting good rocks, but further negative points are withdrawn once the knowledge about any particular rock increases (i.e. entropy < 0.5). In practice this means that during rollouts *check* will be preferred if it reduces entropy for some rock, that *sample* will be preferred when standing over a promising rock, and that otherwise movement actions will be considered.

We compared three different policies: uniformly random with legal moves ("legal" in POMCP), explicit preferred actions ("smart" in POMCP) and our own, "PGS". Figure 3 shows the discounted rewards averaged over 1000 runs for all three policies in *rock-sample* $[11,11]$, $[15,15]$, and the large $[25,25]$ and $[25,12]$, with up to 2048 Monte-Carlo simulations per move.

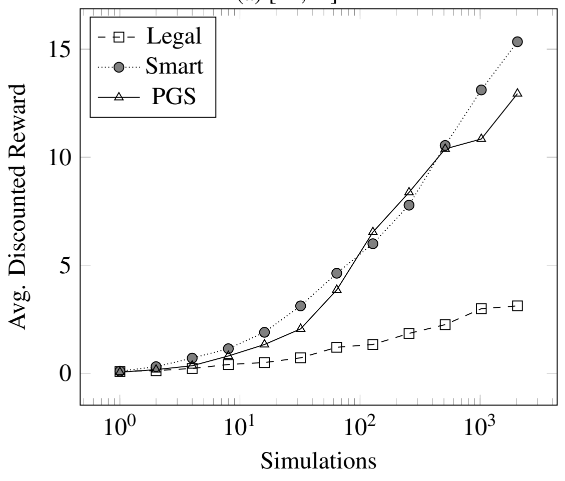
PGS clearly outperforms the legal policy and is only slightly outmatched by the smart policy. This difference however reduces as the problem size in-



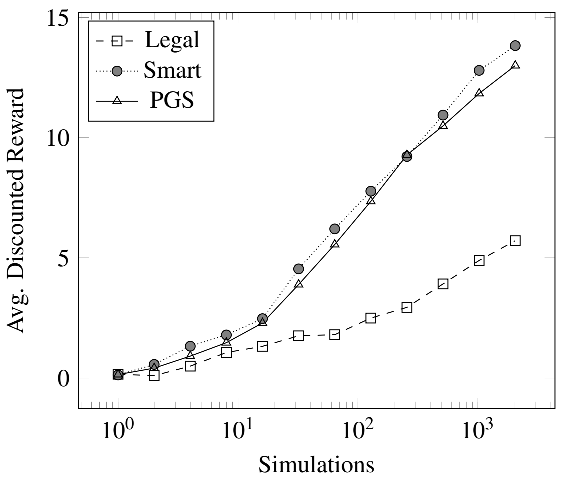
(a) [11,11]



(b) [15,15]



(c) [25,25]



(d) [25,12]

Figure 3: Performance in Rocksample

creases, particularly in $[25,25]$, a very large problem for *rocksample* standards and in $[25,12]$, an equally large grid but with fewer reward sources. Estimating the PGS value of derived states for every action in our rollout policy may be somewhat computationally expensive, particularly when all or many actions are available, since it trades off simulations for runtime. Results show, however, this pays off compared to the random policy: with ≈ 2.5 seconds of computation in *rocksample*$[25,12]$, the legal rollout policy achieves a discounted reward of 5.713 with 2048 simulations, whereas PGS collects 7.35 with only 128 simulations. A faster implementation for planning onboard robots might be necessary, but also a shallower planning depth may be used (the experiments used a depth of 90 steps). Additionally, extensions for estimating the goal proximity of beliefs and not only sampled states (which POMCP does) might be helpful.

6 Conclusions & discussion

Our experimental results show that PGS is useful to improve the performance of planning in large (PO)MDP's, despite its simplicity and even considering the contributions of algorithms such as POMCP, that handle large state spaces relatively well. Planning directly over beliefs might be useful for problems with extreme uncertainty, and where many uncertainty-reducing actions may be necessary as is the case of many robotic planning domains. In fully observable problems such as the Taxi domain, PGS achieved a level of performance that seems unattainable for a uniformly random policy.

In domains with partial and mixed observability and particularly in problems with scarce reward sources, PGS easily outperformed the uniformly random policy. In these scenarios, such policies scale poorly and domain knowledge becomes necessary to achieve good performance. We showed that with barely any domain-dependent knowledge, PGS can be competitive with a manually designed, action selection policy with very detailed, heuristic knowledge. This type of domain-independent bias is essential for planning and acting in complex domains.

In general we can identify three main approaches for speeding up planning in large stochastic domains: 1) Action hierarchies that produce smaller, abstract MDP's and then transfer these solutions to the base MDP. 2) State abstractions that group states together so their values are shared and the values of unknown states, approximated. 3) PBRS, that forces an agent to focus on good action prospects, avoiding potentially costly choices. It seems that for planning domains with high variability it would be difficult to efficiently generate state or action abstractions in advance, and the planner might have to traverse many unique states anyway. Our PGS methodology addresses this issue by attempting to quickly identify reward sources and back propagate scaled partial rewards, using as little domain knowledge as possible but exploiting an agent's knowledge of its own goals. All of the aforementioned techniques are either strongly domain dependent or use fixed criteria to generate groups or categories.

As previously stated, this work is only part of our efforts to introduce the notion of relevance in task planning. Future work includes expanding the formal definition of goal proximity for beliefs, and designing *dynamic* value approximation and/or state aggregation methods derived from this methodology. In order to transfer these methods to real-world robotic tasks, some form of state aggregation or abstraction will be required to map continuous to discrete state representations and to correctly recognize or disregard states with relevant or irrelevant information, respectively. We argue that states should, similar to PGS, be grouped based on criteria derived from the goal.

When thinking about planning and decision problems it is normal to refer to state spaces and the number of states as a measure of their complexity. If we were to compare most MDP benchmark problems with real-world, robotic planning problems, we find that the former often have combinatorial complexity just as games do. We could potentially generate all possible states and therefore, find arbitrarily complex policies. This idea does not transfer well to planning with robots in the "real world", where the number of states may be unknown and, potentially, much larger than a game. Despite these differences, we understand intuitively that some problems can be solved quickly in some level of abstraction and their solutions transferred back to the original domain. So if state complexity does not necessarily represent how complex problems are: how should the complexity of planning problems be estimated? Certainly problems with many states look more complex when only their computational complexity is considered, often a function of the number of states. But more accurately, and because planning problems include not only a domain but also goals, some intrinsic relationship between the values of states and their distance to the goal (or subgoals) must be considered. A good planning algorithm should efficiently identify the gaps in between state values in order to quickly tell apart good states from bad states. These values come uniquely from perceived (or simulated) rewards. Because the value of a state is the average discounted return of its children, it might be hard to differentiate between promising states early on, when the agent is simply too far from any source of reward. Conversely, if the agent always starts next to its goal, the problem should be trivial to solve regardless of the number of possible states. By designing planning algorithms that exploit these observations, we expect to improve the performance of online planning in robots and other agents, despite the apparent complexity of "real-world" domains.

Acknowledgements

This work is supported by a DAAD research grant.

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