Learning Transferable Domain Priors for Safe Exploration in Reinforcement Learning

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Abstract

Prior access to domain knowledge could significantly improve the performance of a reinforcement learning agent. In particular, it could help agents avoid potentially catastrophic exploratory actions, which would otherwise have to be experienced during learning. In this work, we identify consistently undesirable actions in a set of previously learned tasks, and use pseudo-rewards associated with them to learn a prior policy. In addition to enabling safe exploratory behaviors in subsequent tasks in the domain, these priors are transferable to similar environments, and can be learned off-policy and in parallel with the learning of other tasks in the domain. We compare our approach to established, state-of-the-art algorithms in a grid-world navigation environment, and demonstrate that it exhibits a superior performance with respect to avoiding unsafe actions while learning to perform arbitrary tasks in the domain. We also present some theoretical analysis to support these results, and discuss the implications and some alternative formulations of this approach, which could also be useful to accelerate learning in certain scenarios.

1 Introduction

Reinforcement learning (RL) [19] has proven to be a versatile and powerful tool for effectively dealing with sequential decision making problems. In addition to requiring only a scalar reward feedback from the environment, its reliance on the knowledge of a state transition model is limited. This has resulted in RL being successfully used to solve a range of highly complex tasks [21, 13, 17, 14].

However, RL algorithms are typically not sample efficient, and desired behaviors are achieved only after the occurrence of several unsafe agent-environment interactions, particularly during the initial phases of learning. Even while operating within the same domain, commonly undesirable actions (such as bumping into a wall in a navigation environment) have to be learned to be avoided each time a new task (navigating to a new goal location) is learned. This can largely be attributed to the fact that in RL, behaviors are generally learned tabula-rasa (from scratch) [6], without contextual information of the domain it is operating in. This can be limiting when it comes to
deploying RL algorithms in real world systems, where executing sub-optimal actions during learning could be highly dangerous or damaging to the agent or to elements in its environment. Providing RL agents with domain-specific contexts in the form of suitable initializations and/or domain-specific, reusable priors could greatly help mitigate this problem.

The challenge of addressing the issue of avoiding unsafe actions during learning has been the primary focus of the field of safe RL [9], and consequently, a number of methods have been proposed to enable RL agents to learn to solve tasks with due consideration given to the aspect of safety. These methods aim to bias RL agents against such actions, broadly, by means of modifying either the optimization criterion or the exploration process [9]. In either case, the nature of the bias is to directly or indirectly equip the agent with prior information regarding its domain, which is subsequently used to enable safer learning behaviors. Safe RL approaches where such prior knowledge is extracted from already learned tasks in the domain share similarities with the ideology of transfer learning [20]. Perhaps the main distinction between the two is that the former focuses on using domain-specific knowledge to achieve safe behaviors, whereas the focus of the latter is more generally, to reuse previously acquired task knowledge to achieve good performance on a new task.

In this work, we propose an approach to learn a transferable prior for safe exploration by incrementally extracting, refining and reusing common domain knowledge from already learned policies in the domain, an approach consistent with the ideology of continual learning [15]. The reward function used for learning this prior is constructed by approximating rewards from the $Q$-functions of the previously learned tasks for state-action pairs consistently associated with undesirable agent behaviors. Furthermore, as the prior is stored in the form of a $Q$-function, it can be learned off-policy [10], in parallel with an arbitrary task that the agent is learning, without the need for additional interactions with the environment. In addition, it can also be transferred and quickly adapted to other similar environments. The intuition behind our approach is that for a given domain, there exist behaviors that are commonly undesirable to arbitrary tasks in that domain. Learning these behaviors, and incorporating them as prior policies that help bias the agent’s exploratory actions could lead to the safe learning of arbitrary tasks in the domain.

In summary, the main contributions of this work are:

- A novel framework for learning domain priors from previously known tasks.
- A theoretical relation between correctness of a prior and the relative probability of unsafe exploratory actions.
- Experimental results validating the benefits of learning and using the described priors.

2 Related Work

The goal of our approach is to achieve safe exploratory actions during the learning process by making use of existing knowledge of other tasks in the domain, an ideology
that is typical of many transfer RL [20] frameworks. Specifically, we consider the case
where the tasks differ only in the reward functions [4, 12]. In one of the popular ap-
proaches [7] that addressed this case, past policies were reused based on their similarity
to the task being solved. In addition to being able to effectively reuse past policies, the
approach was also shown to be capable of extracting a set of “core” policies to solve
any task in a given domain. A recent method by [11] improved this policy reuse ap-
proach by optimally selecting the source policies online. However, these approaches,
along with several others [16, 18] are only concerned with the problem of reusing past
policies to achieve quicker learning in the target task, without consideration to the cost
of executing poor exploratory actions during learning.

Most approaches that are directly concerned with achieving safe behaviors during
learning, do so by incorporating domain knowledge, and biasing the actions of the
learning agent by modifying either the optimization criterion or the exploration pro-
cess. A detailed summary of such approaches can be found in [9]. Among these, a few
consider the problem of safety at the policy level [5, 2], while others aim to improve
safety at the level of states and actions, much like the approach described in the present
work. The PI-SRL approach by [8] avoids the exploration of unsafe states by using a
known safe baseline policy, coupled with case-based reasoning. However, the main-
tenance of their case-base of known states is based on a Euclidean similarity metric,
which may not be a useful measure in many situations, and hence limits the general-
izability of the approach. Additionally, their assumption regarding the availability of a
safe baseline policy may not be reasonable in many practical circumstances.

The idea of achieving safe learning behaviors by biasing against certain actions has
also been proposed in other recent work. [23] proposed the approach of action elimi-
nation deep Q-networks [13], which essentially eliminates sub-optimal actions, and
performs Q-learning on a subset of the state-action space. The elimination of actions
is based on a binary elimination signal which is computed using a contextual bandits
framework. Similar to this, the idea of shielding was proposed by [1], where unsafe
actions were disallowed based on a shielding signal. The authors synthesize the shield
separately, from a safety game between an environment and a system player. Akin to
these approaches, the basis of our approach is to bias the agent against certain actions
which are considered to be probably unsafe, as per a learned prior policy. However,
the key idea is to learn this prior based on actions that are consistently associated with
poor behaviors, in an online and off-policy manner, without the requirement of addi-
tional interactions with the environment.

3 Methodology

We consider the objective of learning a prior policy \( \pi_P \) by learning the corresponding
Q-function \( Q_P \) in a domain \( D = < S, A, T > \), where the tasks \( M = < D, R > \) share
a common state-space \( S \), action-space \( A \) and state-transition function \( T \), and differ
solely in the reward function \( R \). The purpose of this prior is to bias the learning agent
against unsafe exploratory actions, which we define as follows:

Definition 1. For a task \( M = < S, A, T, R > \) whose optimal Q-function \( Q^* \) is known,
an action $a$ is deemed unsafe in a state $s$ if $a = \arg\min_{a' \in A} Q^*(s, a')$.

The definition implies that in order to determine whether an action is unsafe, the optimal $Q$-function must already be known. Hence, during learning, it is not possible to identify unsafe actions without external knowledge. We incorporate this knowledge via the prior policy, the implicit assumption being that there exists a considerable overlap between the unsafe actions as per this policy, and the policy of the task being learned. The prior policy is learned based on a set of undesirable actions, which we define as follows:

**Definition 2.** The undesirability of an unsafe action $a$ is the absolute value of the optimal advantage $A^*(s, a)$ for that action, where $A^*(s, a) = Q^*(s, a) - \max_{a' \in A} Q^*(s, a')$.

The optimal advantage function $A^*(s, a)$ [3] measures the deviation of the $Q$-value for a particular state-action pair $(s, a)$ from the maximum $Q$-value associated with the state $s$. Thus, $|A^*(s, a)|$ is indicative of how much worse action $a$ is, in relation to the best action in that state.

In order to learn $Q_P$, we assume that we know the optimal $Q$-functions corresponding to $N$ arbitrary tasks in the domain $D$. For the sake of argument, let us consider the case where $N > 1$, which implies there exist at least a few tasks $M = \{M_1, \ldots, M_i, \ldots, M_N\}$ whose optimal $Q$-functions $Q^* = \{Q_1^*, \ldots, Q_i^*, \ldots, Q_N^*\}$ are known. In the proposed approach, $Q_P$ corresponds to a pseudo-task $M_P = \langle D, R_P \rangle$ that is learned off-policy by sampling state-action pairs in the given domain, for example, by executing random exploratory actions in the environment. More practically, they are sampled as per a behavior policy $\pi_B$ corresponding to an arbitrary task $M_\Omega = \langle D, R_\Omega \rangle$, that is being learned in parallel. Although in general, any off-policy approach could be used to learn $Q_P$, here, we use the $Q$-learning algorithm [22].

The basis of our approach is to construct the pseudo-reward function $R_P$ based on state-action pairs that are consistently undesirable across the $N$ known tasks. We infer rewards that would likely be associated with such state-action pairs and subsequently construct $R_P$ as a weighted sum of these inferred rewards. Once $R_P$ is constructed, $Q_P$ is learned off-policy, and is subsequently used to bias the exploratory actions of the agent. Corresponding to this description, our methodology is composed of the following steps:

### 3.1 Identification of suitable state-action pairs

The first step in our approach is to identify state-action pairs that are consistently associated with undesirable agent behaviors. Once a state-action pair $(s, a)$ has been sampled using the agent’s behavior policy $\pi_B$, for each task $M_i$ of the $N$ known tasks, we check whether $a$ is an unsafe action in state $s$. For example, for a known task $M_i$, and state-action pair $(s, a)$, the quantity $d_i(s, a)$ is computed as follows:

$$d_i(s, a) = \begin{cases} 1 & \text{if } a = \arg\min_{a' \in A} (Q_i^*(s, a')) \\ 0 & \text{otherwise} \end{cases}$$

(1)
$d_i(s,a)$ only provides binary information about whether action $a$ was unsafe in state $s$. In order to obtain an idea of the undesirability of the action, we weight $d_i(s,a)$ with the absolute value of the optimal advantage function $A^*_i(s,a)$ associated with the state-action pair:

$$w_i(s,a) = d_i(s,a) |A^*_i(s,a)|$$

We repeat this procedure for each of the $N$ tasks, and store the obtained measures in a sequence $W(s,a)$ as follows:

$$W(s,a) = \{w_1(s,a),...w_i(s,a),...w_N(s,a)\}$$

It is to be noted that $w_i(s,a)$ quantifies the undesirability of action $a$ as per Definitions 1 and 2. In cases where the scale of the $Q$-functions in $Q^*$ varies considerably, weighting $d_i(s,a)$ by the absolute value of the advantage function may skew the true undesirability of the actions. Hence, a more conservative approach would be to directly use $d_i(s,a)$ as a measure of undesirability, such that:

$$W(s,a) = \{d_1(s,a),...d_i(s,a),...d_N(s,a)\}$$

Both formulations perform equivalently in our grid-world experiments, probably because the scale of values of the $Q$-functions we considered did not vary drastically. However, here, we consider the case of Equation 2 due to the fact that it can assume non-binary values, and could thus be more informative.

The overall consensus on the undesirability of action $a$ in state $s$, as per the $N$ known tasks can be measured by quantifying the consistency in the values stored in $W(s,a)$. We do this by converting $W(s,a)$ into a probability distribution $W'(s,a)$ and then measuring the normalized entropy $\mathcal{H}(W'(s,a))$ associated with it:

$$\mathcal{H}(W'(s,a)) = -\sum_{i=1}^{N} \frac{w'_i(s,a) \log(w'_i(s,a))}{\log(N)}$$

where $W'(s,a) = \{w'_1(s,a),...w'_i(s,a),...w'_N(s,a)\}$, and $w'_i(s,a)$, the $i^{th}$ element of $W'(s,a)$, is computed using the softmax function:

$$w'_i(s,a) = \frac{e^{w_i(s,a)}}{\sum_{i=1}^{N} e^{w_i(s,a)}}$$

In order to construct the pseudo-reward function $R_P$, we select state-action pairs which are associated with high values of $w_i(s,a)$, as well as a high normalized entropy value $\mathcal{H}(W'(s,a))$. The former criterion, quantified by the mean $\mu(W(s,a)) = \frac{1}{N} \sum_{i=1}^{N} w_i(s,a)$ of the values in $W(s,a)$, prioritizes state-action pairs that are highly undesirable. The latter criterion $\mathcal{H}(W'(s,a))$ quantifies the consistency of the undesirability of the state-action pair across the known tasks. To account for both these criteria, we use a threshold $t$, and select state-action pairs for which:

$$\mathcal{H}(W'(s,a)) * \mu(W(s,a)) > t$$

The general idea is to select state-action pairs associated with highly and consistently undesirable behaviors across the known tasks in the domain. The selection of
state-action pairs using Equation 6 depends heavily on the choice of a suitable threshold value \( t \), for which a rough guideline can be obtained by considering the ranges of \( H(W'(s, a)) \) and \( \mu(W(s, a)) \). \( H(W'(s, a)) \) lies in the range \([0, 1]\), while the range of \( \mu(W(s, a)) \) depends on that of the advantage function \( A^*(s, a) \). The minimum value of \(|A^*(s, a)|\) is 0, when \( a = \arg\max_{a' \in A} Q^*(s, a') \). The maximum value corresponds to the case when \( Q^*(s, a) \) is as low as possible, and \( \max_{a' \in A} Q^*(s, a') \) is as large as possible.

If \( r_{\min} \) and \( r_{\max} \) represent the lowest and highest possible rewards in the domain, then using the lower and upper bounds of \( \frac{r_{\min}}{1-\gamma} \) and \( \frac{r_{\max}}{1-\gamma} \) for the \( Q^* \)-function, the maximum possible value of \(|A^*(s, a)|\) would be: \( \frac{|r_{\min} - r_{\max}|}{1-\gamma} \). Hence, threshold \( t \) must be selected to be in the range \([0, \frac{|r_{\min} - r_{\max}|}{1-\gamma}]\). By experimenting with different values of \( t \), we found that useful values are much lower than the upper limit of \( \frac{|r_{\min} - r_{\max}|}{1-\gamma} \).

### 3.2 Constructing pseudo-rewards and learning \( Q_P \)

Consider an arbitrary task \( \mathcal{M} \) in the domain for which the policy is learned using \( Q \)-learning. The corresponding standard update equation is given by:

\[
Q(s,a) \leftarrow Q(s,a) + \alpha[r(s,a,s') + \gamma \max_{a' \in A} Q(s',a') - Q(s,a)]
\]

(7)

Here, \( s \) and \( a \) represent the current state and action, \( \gamma \) is the discount factor (\( 0 \leq \gamma \leq 1 \)), \( s' \) is the next state, and \( r(s,a,s') \) is the reward associated with the transition.

When the optimal \( Q^* \)-function is learned, the temporal difference (TD) error: \( [r(s,a,s') + \gamma \max_{a' \in A} Q^*(s',a') - Q^*(s,a)] \) would reduce to 0. Using this fact, we can infer the original reward \( r(s,a,s') \) associated with the transition:

\[
r(s,a,s') = Q^*(s,a) - \gamma \max_{a' \in A} Q(s',a')
\]

(8)

In reality, the above equality seldom holds, as the TD error may not be exactly 0. However, the inferred reward may still be a reasonable approximation if the \( Q \)-function is close to optimal (\( Q \approx Q^* \)). With this assumption in mind, we apply Equation 8 to each of the known tasks, and construct the rewards associated with those state-action pairs \((s_c,a_c)\) which satisfy the condition in Equation 6. The pseudo-reward \( r_P \) is computed as a sum of these inferred rewards, weighted by the corresponding elements of \( W'(s_c,a_c) \):

\[
r_P(s_c,a_c,s'_c) = \sum_{i=1}^{N} w_i(s_c,a_c) [Q_i^*(s_c,a_c) - \gamma \max_{a' \in A} Q_i^*(s'_c,a')] 
\]

(9)

\( r_P \) is capped to have a maximum absolute value of 1, and for state-action pairs that do not satisfy Equation 6, \( r_P \) is set to a default value of 0. \( r_P \) is then used to update the \( Q \)-function \( Q_P \), via the standard \( Q \)-learning update equation (Equation 7). By continuously sampling state-action pairs, determining the corresponding pseudo-reward \( r_P \) and updating \( Q_P \), the optimal \( Q \)-function \( Q_P^* \), is learned. It is worth mentioning that \( Q_P \) is updated using whatever state-action pairs are sampled by the behavior policy.
π_B. Hence, no additional interactions with the environment are required for its computation. However, learning Q_P is subject to the condition that π_B sufficiently explores the state-action space. The additional requirements for learning a prior policy are the additional memory and computations corresponding to inferring r_P, and storing and updating Q_P. The overall process of updating Q_P is summarised in Algorithm 1.

**Algorithm 1** Algorithm for updating prior Q-function Q_P

1: **Input:**
2: Set of N optimal Q-functions Q_∗ = {Q_1, Q_2, ..., Q_N}, Estimate of prior Q-function Q_P, maximum number of steps per episode H, behavior policy π_B, threshold t
3: **Output:** updated estimate of Q_P
4: **for** H steps **do**
5: Execute behavior policy π_B to take action a from state s, and obtain next state s'
6: Initialize W(s,a) as an empty set
7: **for** each task i of the N known tasks **do**
8: Initialize d_i(s,a) as 0
9:  **if** a = argmin_{a' ∈ A} (Q_∗_i(s,a')) **then**
10:  d_i(s,a) = 1
11: **end if**
12: Compute A_∗_i(s,a) = Q_∗_i(s,a) − max_{a' ∈ A} Q_∗_i(s,a')
13: w_i(s,a) = d_i(s,a) |A_∗_i(s,a)|
14: W(s,a) = W(s,a) ∪ w_i(s,a)
15: **end for**
16: Normalize W(s,a) using Equation 5 to obtain W'(s,a) = {w_1(s,a), w_1'(s,a), ..., w_N(s,a)}
17: Compute H(W'(s,a)) (Equation 4)
18: Compute μ(W(s,a)) = 1/N ∑_{i=1}^N w_i(s,a)
19: Initialize pseudo-reward r_P(s,a,s') as 0
20:  **if** μ(W(s,a)) * H(W'(s,a)) > t (threshold) **then**
21: r_P(s,a,s') = 1/N ∑_{i=1}^N w_i'(s,a)[Q_∗_i(s,a) − γ max_{a' ∈ A} Q_∗_i(s',a')]
22:  **end if**
23: Q_P(s,a) ← Q_P(s,a) + α[r_P(s,a,s') + γ max_{a' ∈ A} Q_P(s',a') − Q_P(s,a)]
24: **end for**

### 3.3 Biasing exploration using Q_∗_P

Q_∗_P is learned based on a reward function R_P, which is specifically constructed using state-action pairs that are consistently associated with poor agent behaviors. Hence, in order to avoid catastrophic actions during learning, we simply bias the agent’s behavior against taking actions that are unsafe, as determined by Q_∗_P. If such an action happens
to be suggested by the agent during learning, with a high probability $\rho$, we disallow it from being executed, and force the agent to pick suitable alternative. Algorithm 2 outlines the process of biasing the agent against unsafe exploratory actions.

Algorithm 2 Biasing against unsafe exploratory actions

1: **Input:**
2: Proposed exploratory action $a_0$, state $s$, optimal $Q$- function of prior $Q_P^*$, probability of using priors $\rho$
3: **Output:** selected action $a$
4: With a probability $\rho$
5: while $a_0 = \arg\min_{a' \in A} Q_{P}^{*}$ do
6: Pick random action from $A : a_0 = \text{random}(A)$
7: end while
8: $a = a_0$

4 Theoretical Analysis

The effectiveness of biasing the exploratory actions as described is highly dependent on how correct the learned priors are. In this section, we derive a relation between the correctness of a prior and the probability of taking unsafe actions using our approach, relative to an $\epsilon$-greedy exploration policy. We first define the correctness of a prior as follows:

**Definition 3.** The correctness $C_{Q_P,D}$ of a prior $Q_P$, with respect to a domain $D$ is the probability with which it avoids deeming an action to be safe, when it is actually unsafe.

$$C_{Q_P,D} = 1 - \frac{n_{FN}}{n_{I} - n_{FP} + n_{FN}}$$

where $n_{FP}$ and $n_{FN}$ are respectively the number of false positives (cases where the action has been incorrectly classified by $Q_P$ as unsafe) and false negatives (cases where the action has been incorrectly classified by $Q_P$ as safe), and $n_I$ is the number of unsafe actions identified by $Q_P$. It is worth noting that only the false negative cases affect the probability of encountering truly unsafe actions. The effect of false positives would be to simply slow down learning. The extent to which the correctness $C_{Q_P,D}$ affects the probability of encountering unsafe actions, relative to the case of $\epsilon$-greedy exploration, is presented in the following theorem:

**Theorem 4.** If a prior $Q_P$ with a correctness of $C_{Q_P,D}$, is used to bias the exploratory actions with a probability of $\rho$, then relative to the case of standard $\epsilon$-greedy exploration, the expected number of unsafe exploratory actions is reduced by a factor of

$$1 - \frac{\rho|A|C_{Q_P,D}^-1}{|A|-1}$$

where $A$ is the action space associated with the domain.

**Proof.** For the case of standard $\epsilon - greedy$ exploration, the agent takes exploratory actions with a probability of $\epsilon$, in each instance of which, the probability of picking
an unsafe action is \( \frac{1}{|A|} \). Hence, the probability of unsafe exploratory actions for an \( \epsilon - greedy \) strategy is: 

\[
p_{\epsilon-\text{greedy}} = \frac{\epsilon}{|A|}
\]

Now, in the case of biased exploration, exploratory actions occur with a probability of \( \epsilon \), and are biased using the priors, with a probability \( \rho \). When the bias is used, the agent eliminates at least one unsafe action (as determined by \( Q_P \)), and uniformly and randomly selects from the remaining \(|A| - 1\) actions. However, the selected action may still be unsafe due to the presence of false negatives, which occur with a probability of \( 1 - C_{Q,P,D} \). With the remaining probability of \((1 - \rho)\), exploration occurs exactly as in the \( \epsilon - greedy \) case. Hence, the total probability of unsafe actions occurring during exploring is: 

\[
p_{\text{priors}} = \frac{\rho (1-C_{Q,P})}{|A|-1} + \frac{(1-\rho)}{|A|}.
\]

The ratio \( \frac{p_{\text{priors}}}{p_{\epsilon-\text{greedy}}} \) can then be simplified to: 

\[
1 - \frac{\rho (|A| C_{Q,P} - 1)}{|A|-1}
\]

This implies that fewer unsafe actions can be expected when \( C_{Q,P,D} > 1/|A| \) and \( \rho \) is large. Although a large value of \( \rho \) is favorable, in order to maintain a non-zero probability of visiting every state-action pair (and thus ensure convergence), it is set to be slightly less than 1.

### 5 Results

We demonstrate our approach on a version of the 21 \( \times \) 24 grid-world navigation environment, first proposed by [7]. Each state is represented by a 1 \( \times \) 1 grid cell, with darker colored cells representing obstacles, and other cells representing free positions. The agent’s state is represented by its \((x, y)\) coordinates, and at each state, it is allowed to take one of four actions - moving up, down, left or right. Following the execution of an action, the agent moves to a new state, which is noised by random values sampled from a uniform distribution in the range (-0.2,0.2).

When the agent executes an action that causes it to bump into an obstacle, it retains its original state, without moving. The original environment in [7] was set up such that the agent received 0 rewards for such transitions. However, this type of reward structure is not suited to the study of safe behaviors, as undesirable actions such as bumping into walls are not penalized. Hence, we use a modified reward structure in which such transitions are associated with a reward of \(-1\). Goal states are terminal, and transitions leading into them are associated with a reward of 1. For all other transitions, the agent receives a small negative reward of \(-0.1\). This penalises behaviors such as moving back and forth between two non-goal states.

For each task, the agent is allowed to interact with the environment for \( K \) episodes. Each episode starts with the agent in a random, non-goal state, following which, it could execute up to \( H \) actions to try and reach the terminal goal state. The performance \( W \) of the agent is evaluated by computing the discounted sum of rewards per episode as follows:

\[
W = \frac{1}{K} \sum_{k=0}^{K} \sum_{h=0}^{H} \gamma^h r_{k,h}
\]

where \( r_{k,h} \) is the reward received from the environment at step \( h \) of episode \( k \).
5.1 Performance comparison

To demonstrate the learning of priors and their influence on learning new tasks, we consider the environment shown in Figure 1, in which the optimal policies corresponding to tasks $M_{\Omega_1}$, $M_{\Omega_2}$, $M_{\Omega_3}$ and $M_{\Omega_4}$ are known. In Figure 1, corresponding labels are used to mark the goal locations of these tasks. The label $\Omega_T$ marks the goal location of the target task $M_{\Omega_T}$, which the agent aims to learn.

![Figure 1: Navigation environment showing the goal locations $\Omega_1, \Omega_2, \Omega_3, \Omega_4$ of the known tasks, and goal location $\Omega_T$ of the task to be learned.](image)

The prior is learned using the optimal $Q$-functions of tasks $M_{\Omega_1}$, $M_{\Omega_2}$, $M_{\Omega_3}$ and $M_{\Omega_4}$, as described in Algorithm 1. Figure 2 depicts the set of consistently undesirable actions identified using these known tasks, which is then used for learning the prior $Q_P$. The red, green, blue and orange arrows represent actions that move the agent up, right, down and left respectively. As observed in Figure 2, most of the identified actions correspond to those that would cause collisions with obstacles in the environment. The task $M_{\Omega_T}$ is learned by biasing the exploratory actions of the agent using the learned prior, as described in Algorithm 2.

Figure 3 shows the average performance over 10 trials, of different algorithms, evaluated using Equation 10. The shaded regions represent the standard errors of the mean performances for the 10 trials. The common learning parameters were set as follows: $\alpha = 0.05$, $\gamma = 0.95$, $H = 500$, $K = 2000$, and the probability of exploration $\epsilon$ was set to be decaying from an initial value of 1, as in [7]. Two of the performance curves in Figures 3 and 4 were obtained by combining the described approach with: a) standard $Q$-learning [22], and b) PRQ-learning (PRQL) [7]$(\psi = 1, \nu = 0.95)$. The parameters specific to our approach were chosen to be: $t = 0.5$, $\rho = 0.95$. As observed from the figure, these curves exhibit a superior learning performance compared to their corresponding counterparts, in which the learning occurs without the use of domain priors. In particular, the use of learned priors enables a significant increase in the initial performance of the agent, due to fewer unsafe exploratory actions during the initial phases of learning. This is supported by the results in Figure 4, which depicts the trend...
in the percentage of unsafe actions per episode in each of the tested approaches. The overall performance of the agent is also superior to other approaches such as the OPS-TL approach \[11\] \((c = 0.0049)\) for selecting source tasks, and the PI-SRL approach \[8\] \((k = 6, \sigma = 0.5)\), in which safe exploratory actions are chosen based on case-based reasoning. Although the latter approach has a marginally better initial performance as seen in Figure 3, the learned policy is very conservative, as indicated by the negligible improvement in its performance across the episodes. From these figures, it is evident that the use of domain priors brings about improvements in both safety as well as learning performance.

5.2 Adapting priors to different environments

The priors described in the previous section can effectively help avoid undesirable exploratory actions while learning an arbitrary task in the domain. However, if the environment was to undergo a change in configuration, the set of actions associated with unsafe agent behaviors would not remain the same. Nevertheless, provided these changes are not too drastic, the priors learned from the original environment could still serve as a useful initialization for learning the corresponding priors in the modified environment. In other words, the priors may be transferable to the modified environments.

We demonstrate this transferability in modified versions of the original environment in Figure 1, shown in Figures 5(a)-(d). The environments in Figures 5(a)-(c) are obtained by either adding or removing obstacles to/from the original environment, whereas the environment in Figure 5(d) is created by offsetting most obstacles 2 units upwards and to the right. The consistently undesirable actions for the original environment in Figure 1 are overlayed on top of the modified environments in Figures 5(a)-(d), whereas the correct set of consistently undesirable actions for the modified environments are shown in Figures 5(e)-(h). Despite the differences between the undesirable
actions of the original and modified environments, there exists some structural similarity between them. Hence, it is reasonable to expect the priors learned in the original environment to be at least partially transferable to the modified environments. Specifically, we posit that the learned prior for the original environment forms a reasonable initial estimate for learning the corresponding priors in the modified environments, as long as the differences between the two are not drastic.

In order to test this hypothesis, the priors for the modified environments were learned with and without these initial estimates. In both cases, the associated absolute TD errors decrease, as shown in Figures 5(i)-(l), which demonstrates the capability of the priors to adapt to different environments. Figures 5(i)-(k) suggest that initialization of the priors could lead to significantly lowered initial absolute TD errors compared to the case of learning the priors from scratch (without initialization). However, initializing the priors in this manner was not found to be useful for the environment in Figure 5(d), where the effect of the initialization was to increase the initial absolute TD error, as depicted in Figure 5(l). This is due to the fact that the nature of the differences in the obstacle configuration in Figure 5(d) and Figure 1 renders the prior learned in the latter ineffective with respect to learning the prior in the former. These experiments demonstrate that while the prior learned using the described approach is transferable to some extent, it is not transferable in general.
Figure 4: The percentage of obstacle collisions, computed over 10 trials, for different learning methods.

6 Discussion

The proposed methodology allows RL agents avoid undesirable actions during learning by making use of a learned prior policy. Although our approach as described, deals with avoiding undesirable actions, it can be easily adapted to scenarios where there exist actions that are commonly desirable across the tasks in the domain. Such an adaptation would involve replacing the advantage $A^*_i(s, a)$ with $B^*_i(s, a) = Q^*_i(s, a) - \min_{a' \in A} Q^*_i(s, a')$, in addition to replacing the $\arg\min$ in Equation 1 with $\arg\max$, and Equation 2 with $w_i(s, a) = d_i(s, a) |B^*_i(s, a)|$. The resulting prior could then simply be used to guide exploration, by taking exploratory actions that are greedy with respect to $Q^*_P$, with a high probability. Such an approach appeared to be successful in versions of the grid-world environment where a non-goal, rewarding state was introduced into all tasks in the domain (details provided in the supplementary material). Although the approach is useful for such specific situations, in general, exploring the state-action space by greedily exploiting the prior in this manner could lead to poor learning performances. Hence, achieving safe learning behaviors is a more practical use-case for the approach described in this work.

The ability to avoid undesired/unsafe actions during learning makes the proposed approach potentially useful for real-world systems which are often intolerant of poor actions. Our approach would thus be useful in scenarios where the associated marginal increase in memory and computational costs are outweighed by the costs of executing unsafe actions. In addition, we expect the described ideas and formulation to carry over to continuous environments.
Figure 5: (a)-(d) show the consistently undesirable actions corresponding to the original environment in Figure 1, overlayed on top of four modified environments. (e)-(h) show these environments, with actions that are actually undesirable in them. (i)-(l) show the absolute TD errors associated with the learning of $Q_P$ for these environments, with and without prior initialization.

Although we only consider cases where tasks vary solely in the reward function, this could lay the foundation for more general work, where tasks vary in other aspects such as the representation, transition function or the state-action space.

7 Conclusion

We presented a method to extract priors from a set of known tasks in the domain. The prior is learned in the form of a $Q$-function, and is based on inferred rewards corresponding to consistently undesirable actions across these tasks. The effectiveness of the prior to enable safe learning behaviors was demonstrated in a navigation environment, and its performance was compared to other similar approaches. This was further supported by our theoretical analysis, which suggests that the use of these priors helps reduce the probability of taking unsafe exploratory actions. In addition to leading to
safer learning behaviors for arbitrary tasks in the domain, the priors were shown to be transferable to some extent, and capable of adapting to changes in the environment.

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Supplementary material:

8 Application to common reward case

In domains where there exists a common, non-terminal rewarding state $s_{com}$, the proposed approach can be modified to positively bias the agent towards taking greedy actions with respect to the learned prior $Q_p$, as described in the discussion section. By doing so, we shift the focus of the algorithm to finding consistently desirable actions across the known tasks in this common reward environment. Here, we present one such environment, where in addition to the attributes of the environment in Figure 1, there exists a non-terminal rewarding state $s_{com}$ associated with a reward of 0.2. In such a case, visiting state $s_{com}$ becomes a desirable behavior across all tasks. Hence, the learned prior directs learning agents towards this state, as seen in Figure 7. Such a bias in the exploration policy is also reflected in the performance of the agent, as depicted in Figure 8.

![Navigation environment](image)

Figure 6: Navigation environment showing the goal locations $\Omega_1, \Omega_2, \Omega_3, \Omega_4$ of the known tasks, common rewarding state $s_{com}$ and goal location $\Omega_T$ of the task to be learned.
Figure 7: Identified desirable actions for the common reward environment in Figure 6.

Figure 8: The average discounted return per episode ($W$), computed over 10 trials, for different learning methods.