Learning and Solving Regular Decision Processes

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Abstract

Regular Decision Processes (RDPs) are a recently introduced model that extends MDPs with non-Markovian dynamics and rewards. The non-Markovian behavior is restricted to depend on regular properties of the history. These can be specified using regular expressions or formulas in linear dynamic logic over finite traces. Fully specified RDPs can be solved by compiling them into an appropriate MDP. Learning RDPs from data is a challenging problem that has yet to be addressed, on which we focus in this paper. Our approach rests on a new representation for RDPs using Mealy Machines that emit a distribution and an expected reward for each state-action pair. Building on this representation, we combine automata learning techniques with history clustering to learn such a Mealy machine and solve it by adapting MCTS to it. We empirically evaluate this approach, demonstrating its feasibility.

1 Introduction

In the emerging area of personal health tracking, one records one’s pulse, blood pressure, glucose levels, activity levels, nutritional information and much more, in an attempt to learn how to improve one’s physical and mental health. In this domain, the state of many variables of interest and the effects of various actions are most likely not Markovian functions of the value of the most recently measured variables. Hence, applying standard, MDP-based, RL algorithms [Sutton and Barto, 1998] to a state model consisting of the value of these observed variables will most likely lead to sub-optimal behavior.

Motivated by such application domains, Regular Decision Processes (RDPs) [Brafman and De Giacomo, 2019] have been recently introduced as a non-Markovian extension of MDPs that does not require knowing or hypothesizing a hidden state. An RDP is a fully observable, non-Markovian model in which the next state and reward are a stochastic function of the entire history of the system. However, this dependence on the past is restricted to regular functions. That is, the next state distribution and reward depends on which regular expression the history satisfies.

An RDP can be transformed into an MDP by extending the state of the RDP with variables that track the satisfaction of the regular expression governing the RDP dynamics. Thus, essentially, to learn an RDP, we need to learn these regular expressions. For example, in the context of personal health-tracking, one might learn which sequences of activities and measurements make a state of hyperglycaemia, hypoglycaemia, or depression, likely, and consequently, adapt behavior policies that prevent them.

An optimal policy for an RDP is a mapping from regular properties of history to actions. Thus, it provides users with clear, understandable guidelines, based on observable properties of the world, in contrast to, e.g., arbitrary hidden states in a learned POMDP, or unclear features in a neural network.

This paper makes two contributions to the emerging theory of RDPs. Our first contribution is the use of a deterministic Mealy Machine to specify the RDP. For each state and action, this Mealy machine emits as its output, a class label. This class label is associated with a distribution over the underlying system states and a reward signal. This idea extends the use of Mealy Machines to specify non-Markovian rewards, introduced recently by [Camacho et al., 2019], to RDPs. Our second, and main contribution is to use this idea to formulate the first algorithm for learning RDPs from data, and to evaluate it on two non-Markovian domains. Our algorithm identifies, through exploration, histories that have similar dynamics based on their empirical distributions and then learns a Mealy Machine that outputs, for each history, an appropriate label. Then, we solve this Mealy Machine to obtain an optimal policy. This can be done by either reducing it to an explicit MDP, or by using the Mealy Machine to provide the distributions needed for running MCTS [Kocsis and Szepesvári, 2006; Silver and Veness, 2010]. This algorithm was implemented and tested on two domains modelled as RDPs, demonstrating its ability to learn RDPs from observable data and to generate a near-optimal policy for these models.

2 Background

We assume familiarity with MDPs, recalling basic notation only. We briefly discuss NMDPs, RDPs, and Mealy Machine.

2.1 MDP and NMDPs

A Markov Decision Process (MDP) is a tuple $M = (S, A, Tr, R, s_0)$. $S$ is the set of states, $A$ a set of actions, $Tr : S \times A \rightarrow \Pi(S)$ is the transition function that returns for every state $s$ and action $a$ the distribution over the next state.
A Regular Decision Processes (RDP) \cite{Brafman and De Giaccomo, 2019} is a factored NMDP in which the dependence on history is restricted to regular functions. By factored, we mean that its states consist of assignments to state variables and the transition function exploits this structure. Here, we assume Boolean state variables for convenience. To specify the dependence of the transition and reward on the history, we assume formulas to specify sets of histories. Histories are essentially strings over an alphabet of states (for convenience, we can assume that the last action executed is part of the state). Regular expressions (RE) are an intuitive and much used language for specifying languages, i.e., sets of strings. However, they do not have the logical structure to exploit more fine-grained properties of the internal assignments of a state, and do not efficiently support various useful operations on sets of strings. Linear dynamic logic on finite traces (LDF) \cite{De Giacomo and Vardi, 2013} combines linear-time temporal logic (LTL) with the syntax of propositional dynamic logic (PDL) but interpreted over finite traces. LDF has the same expressive power as RE, allows us to refer to properties of states, and supports simple specification of conjunction, disjunction, and negation. RDPs use LDF formulas to specify properties or classes of histories. To simplify their exposition, in this paper we do not make explicit use of them, and it is enough to know about RE and to think of each formula we mention as specifying an RE. For more details, see \cite{Brafman and De Giaccomo, 2019}.

An RDP is a tuple \( M = \{ P, A, S, Tr, R, s_0 \} \). \( P \) is a set of propositions inducing a state-space \( S \) with \( s_0 \) as the initial state. \( A \) is the set of actions. \( Tr \) is a transition function represented by a finite set of quadruples of the form: \( (\varphi, a, P', \pi(P')) \). \( \varphi \) is an LDF formula over \( P \), \( a \in A \), \( P' \subseteq P \) is the set of propositions affected by \( a \) when \( \varphi \) holds, and \( \pi(P') \) is a joint-distribution over \( P' \) describing its post-action distribution. The basic assumption is that the value of variables not in \( P' \) is not impacted by \( a \).

If \( \{ (\varphi_i, a, P'_i, \pi_i(P'_i)) | i \in I \} \) are all quadruples for \( a \), then the \( \varphi_i \)'s must be mutually exclusive, i.e., \( \varphi_i \land \varphi_j \) is inconsistent, for \( i \neq j \). We also assume that the formulas are exhaustive.

Letting \( s_{P'} \) denote \( s' \) projected to \( P' \), \( Tr_L \) is defined as follows: \( Tr_L((s_0, \ldots, s_k), a, s') = \pi(s'_{P'}) \) if quadruple \( (\varphi, a, P', \pi(P')) \) is the (single) one s.t. \( s_1, \ldots, s_k \models \varphi \) and \( s_k \) agrees on all variables in \( P \setminus P' \).

That is, given current trace \( s_0, \ldots, s_k \) and action \( a \) let \( (\varphi, a, P', \pi(P')) \) the quadruple with a condition \( \varphi \) that is satisfied by \( s_0, \ldots, s_k \) (by assumption, exactly one such \( \varphi \) exists). \( s' \) is a possible next state only if it assigns propositions not in \( P' \) exactly the same value to as does \( s_k \), i.e., they are not impacted by the action. Then, the probability that \( s' \) is the next state equals the probability \( \pi \) assigns to the value of the \( P' \) propositions in \( s' \).

The reward function \( R_L \) is specified via a finite set \( R \) of pairs of the form \( (\varphi, r) \). \( \varphi \) is an LDF formula over \( P \), and \( r \in \mathbb{R} \) is a real-valued reward. Given a trace \( s_0, \ldots, s_k \), the agent receives the reward: \( R_L((s_0, \ldots, s_k)) = \sum (\varphi, r) \in R, s_0, \ldots, s_k \models \varphi, r \).

By definition \( R_L \) is bounded above and below.

### 2.3 Mealy-Machine

A Mealy machine is a deterministic finite-state transducer whose output values are determined both by its current state and the current inputs. Formally, a Mealy Machine is a tuple \( M = (S, s_0, \Sigma, \Lambda, T, G) \). \( S \) is the finite set of states, \( s_0 \) is the initial state. \( \Sigma \) is the input alphabet and \( \Lambda \) is the output alphabet. The transition function \( T : S \times \Sigma \rightarrow S \) maps pairs of state and input symbol to the corresponding next state. The output function \( G : S \times \Sigma \rightarrow \Lambda \) maps pairs of state and input symbol to the corresponding output symbol.

### 3 Representing and Solving RDPs

Let \( \varphi_1, \ldots, \varphi_f \) be the set of LDF formulas that specify the transitions and rewards of an RDP. This set is finite because \( T \) and \( R \) are finite. Since each formula is equivalent to an RE, there is an automaton that can track its satisfaction \cite{Baier et al., 2008; De Giacomo and Vardi, 2013}. The automaton’s input alphabet is the product of the sets of RDP states and actions, and it accepts a history IFF it satisfies the corresponding formula. Let \( M_t \) be the automaton tracking \( \varphi_i \). Let \( M = \otimes M_t \) be the product automaton of all the \( M_t \)'s. This automaton will be at an accepting state of exactly one of its transition tracking components given any string because the transition formulas are mutually exclusive and exhaustive. In addition, some reward tracking automata may also accept.

Building on the idea of using Mealy Machines to specify non-Markovian rewards \cite{Camacho et al., 2019}, our key observation is that an RDP can also be specified by a Mealy Machine. The machine’s input alphabet is the product of the sets of RDP states and actions. Its output function assigns to each triple of machine state \( s_{MD} \), RDP state \( s_{RDP} \) and action \( a \), a set of propositions, \( P_{MD \times RDP \times a} \subseteq P \), a distribution over their value in the next RDP state, and a reward.

Such a Mealy Machine represents an RDP because we can reconstruct the RDP from it as follows: Given history \( h \), let
\(s(h)\) be the Mealy Machine state reached on string \(h\) from its initial state. Let \(s_{RDP}\) be the current RDP state. The Mealy Machine output \(G(h(s), (s_{RDP}, a))\) provides us with a specification of the transition function and reward for history \(h \cdot s_{RDP}\) and action \(a\).

The Mealy Machine \(M_{Me}\) that describes an RDP is constructed from the product automaton \(M\) defined above by adding to it an output function. Let \(s = (s_1, \ldots, s_k, \ldots, s_n)\) be a state of \(M\), such that \(M_0\) is the (only) transition tracking automaton in an accepting state. That is \(s_0\) is an accepting state of \(M_0\). Let \(\varphi_k\) be the formula which \(M_0\) accepts, and let \((\varphi_k, a, P', \pi(P'))\) be the corresponding quadruple. Let \(r\) be the sum of rewards associated with all the reward tracking automata that are in an accepting state in \(s\). Define \(G(s_{Me}, (s_{RDP}, a)) = ((P', \pi(P')), r)\), i.e., the propositions and distributions associated with \(\varphi_k\) and the sum of rewards of accepting reward-tracking automata.

The correctness of this construction follows from the definition of RDPs and the correctness of the construction of automata tracking the satisfiability of LDL\(_I\) formulas. The main benefit of this representation of an RDP is that it can serve as a target for learning algorithms that use existing methods for learning Mealy Machines, as we do in Section 4.

To solve an RDP, we can transform it into an MDP \(M_{MDP}\) by taking the product of \(M_{Me}\) with the original state space \(S_{RDP}\) of the RDP [Brafman and De Giacomo, 2019]. The \(M_{Me}\) state reflects the relevant aspects of the entire history. Every \(s_{RDP} \in S_{RDP}\) and \(a \in A\) transform \(M_{Me}\) deterministically, but induce a Markovian stochastic transition over \(S_{RDP}\). \(M_{MDP}\)'s reward function is fully specified given the \(M_{Me}\)'s state, the current RDP state, and the current action. \(M_{MDP}\) can be solved using standard MDP solution techniques [Puterman, 2005]. We use UCT [Kocsis and Szepesvári, 2006], an MCTS algorithm, because MCTS can be applied to RDPs without generating \(M_{MDP}\) explicitly. We maintain the current RDP state, i.e., the most recent set of observations, and the state \(s_{Me}\) of the Mealy Machine. From \(s_{Me}\), for each action and current RDP state, we can obtain as output the information needed to sample the next set of observations and rewards. The new observations replace the old ones, and are used (with the action) to update the Mealy Machine. The choice of which action to apply follows the standard UCB\(_1\) criterion [Auer et al., 2002].

\[ a = \arg\max_a Q(s_{Me}, a) + c \cdot \sqrt{\frac{\log n(s_{Me})}{n(s_{Me}, a)}} \]

with \(s_{Me}\) used here instead of the current RDP state as it captures all history dependent properties of interest.

### 4 Learning RDPs

MDP learning algorithm rely on the Markov assumption and full observability of the state for their correctness. These algorithms are not suitable for learning non-Markovian models, such as an RDP. Instead, we can exploit the alternative, Mealy Machine representation of RDPs and use Mealy Machine learning algorithms to learn the RDP model. More specifically, we use Flexfringe [Verwer and Hammerschmidt, 2017] (using EDSM with the Mealy Machine heuristic) to learn a Mealy Machine that represents the underlying RDP. Then, we use MCTS to generate an optimal policy for the learned model.

#### Algorithm 1 Sample Merge Mealy Model (S3M)

**Input:** domain

**Parameter:** min_samples

**Output:** \(M\)

```
1: Initialize state space of \(M\) to RDP state space \(S_{RDP}\)
2: repeat
3: Set \(S = \text{sample}(domain)\).
4: Set \(Tr = \text{base_distributions}(S, \text{min_samples})\)
5: best_loss = \(\infty\)
6: for \(\epsilon\) in possible epsilons do
7:    \(Tr' = \text{merger}(Tr, \epsilon)\)
8:    loss = \text{calc_loss}(Tr', S)
9:    if loss < best_loss then
10:       \(Tr = Tr'\)
11:       best_loss = loss
12: end if
13: end for
14: \(Me = \text{mealy_generator}\)
15: Set \(S = \langle P, A, S_{Me}, R, R_0(\langle s_0_M, s_{0Me} \rangle)\rangle\)
16: until Max_Iterations
17: return \(M\)
```

Thus, our approach can be characterized as a Model-based RL algorithm for non-Markovian domains.

### 4.1 Learning Algorithm Overview

Algorithm 1 provides the pseudo-code of our learning algorithm S3M (Sample, Merge, Mealy Machine). The next subsections describe each step in detail.

A Mealy Machine learning algorithm expects input of the form (input sequence, output), where output can be the last output following this input sequence. Thus, in our case, we need to generate inputs of the form \((\pi, \alpha)\), where \(\pi\) is a trace and \(\alpha\) is a distribution over the next observation (RDP state) and reward. To create this input, we first generate traces from the RDP by interacting with the environment (Line 3). These traces are traces of the form \(o_0, o_1, r_1, o_2, \ldots, o_k, r_k, o_k\), where \(o_i\) is the action executed at the \(i^\text{th}\) step, \(r_k\) is the reward received following its execution, and \(o_1\) is the next RDP state. We use \(o_1\) to denote the RDP state to stress that it is fully observable.

To transform these traces to pairs of the form \((\pi, \alpha)\), we first identify a set of histories for which we have enough samples \((\geq \text{min_samples})\). We refer to the empirical next-state distributions associated with these histories as base distributions (L. 4). Next, in Lines 6-12, the rest of the histories are merged with the closest history based on the distance of their distribution from one of the base distributions. The merge choice depends on a parameter \(\epsilon\), and we try a range of possible \(\epsilon\) values, attempting to balance model size and accuracy. Associating each of the resulting distribution with some symbol, we can now provide the needed input to the Mealy Machine learning algorithm in the form of pairs (trace, distribution) (L.14). Finally, by taking the product of the learned Mealy Machine with the RDP’s state space, we obtain an MDP that can be solved for an optimal policy.

We repeat this process multiple times, each time with a more informed state space. Initially, we use the RDP state space to guide exploration. Once we learn a Mealy machine,
or improve our current Machine, we update the state space to reflect our new model to help better guide exploration.

4.2 Sampling
To learn the SDR model we need to generate sample traces. We considered two methods for doing this. One is purely exploratory and does not attempt to exploit during the learning process, while the other does.

The Pure Exploration approach uses a stochastic policy that is biased towards actions that were sampled less. More specifically, for every \( a \in A \) and \( s \in S_{RDP} \), where \( S_{RDP} \) is the RDP state space, define:

\[
P(a|s) = \frac{f(a,s)}{\sum_a f(a,s)} \quad \text{where} \quad f(a,s) = 1 - \frac{n(a,s)}{\sum_a n(a,s)}
\]

(1)

Here, \( n(a,s) \) stands for the number of times action \( a \) was performed in state \( s \) of the RDP. This distribution favours actions that were sampled fewer times in a state.

The Smart Sampling approach is essentially Q-learning [Watkins and Dayan, 1992] with some exploration using the above scheme. Specifically, \( Q \) values are maintained for each state-action pair, where states are defined and updated as above, starting with a single-state Mealy Machine. \( Q(s,a) \) is initialized to 0 for all states and actions, and are updated following each sample of the form \( s,a,r,s' \) using \( Q(s,a) = Q(s,a) + \alpha (R(s,a) + \gamma \max_{a' \in A} Q(s',a') - Q(s,a)) \).

With probability \( 1 - \epsilon \), we select the greedy action in state \( s \), and with probability \( \epsilon \) we sample an action based on the distribution defined in Equation (1).

4.3 Trace Distributions
Next, we associate with every trace encountered a set of propositions and a distribution over their probability. (Note that each prefix of a trace is also a trace.) Let \( h = (o_1a_1, o_2a_2, \ldots, o_na_n) \) be a given trace. We define \( P_{h,(o,a)} \), the set of propositions affected by action \( a \) given history \( h \cdot o \), to be all propositions \( p \in P \) such that there exists a trace \( hoo' \cdot o' = (o_1a_1, o_2a_2, \ldots, o_n a_n, o, a, o', o') \) in our sample where \( o \) and \( o' \) differ on the value of \( p \). We expect \( P_{h,(o,a)} \) to be small, typically, because action effects are usually local. Next, we compute the empirical post-action distribution over \( P_{h,(o,a)} \) for history \( h \), RDP state \( o \) and action \( a \). That is, the frequency of each assignment to \( P_{h,(o,a)} \) in the last RDP state over traces of the form \( hoo' \) in our sample.

4.4 Merging Histories and Their Distributions
By modeling a domain as an RDP, our basic assumption is that what dictates the next state distribution of a history is the class of regular expressions it belongs to. Hence, many different histories are likely to display similar behavior because they are instances of the same regular expression. Of course, we do not know what these regular expressions are, and because of the noisy nature of our sample, we cannot expect two histories that belong to the same class to have the same empirical distribution. Moreover, many histories will be sampled rarely, in which case their empirical next-state distribution is likely to significantly differ from the true one. For this reason, we attempt to cluster similar histories together based on their empirical next-state distribution, using KL Divergence [Kullback and Leibler, 1951] as a distance measure. However, we consider merging only histories that affect the same set of propositions.

Our goal is to create clusters s.t. each cluster represents a certain distribution and each trace is assigned to a single cluster. We create the clusters bottom-up. First, we create a single cluster for each trace \( hoo \) as described in 4.2. Each such cluster has also a weight \( w \) denoting the number of samples used to create it. Then, for every two clusters with distributions \( P_1 \) and \( P_2 \) (affecting the same propositions) with weights \( w_1 \geq w_2 \geq \min_{\text{samples}} \), we merge them if:

1. The support of \( P_2 \) contains the support of \( P_1 \)
2. \( D_{KL}(P_1||P_2) \leq \epsilon \)

Note that condition 1 is required for \( D_{KL} \) to be well defined.

The new cluster has weight \( w = w_1 + w_2 \) and a distribution \( P \) such that:

\[
P(\cdot) = (1/\lambda)[w_1 \cdot P_1(\cdot) + w_2 \cdot P_2(\cdot)]
\]

(2)

If a cluster has multiple other clusters with which it can merge, then the one with the smallest KL divergence is selected. We repeat this procedure until no mergers are possible.

Next, for each distribution \( P \) whose weight \( < \min_{\text{samples}} \), we find the distribution \( Q \) from the above clusters that affects the same set of propositions such that \( D_{KL}(P||Q) \) is well defined and minimal, and merge the two using Equation (2) to obtain the new distribution. Notice that such a merge implies that the support of \( P \) is a subset of the support of \( Q \).

The above is repeated for different values of \( \epsilon \), resulting in different models. We now explain how we select the final model. Each model has the form \((\Pi, Tr)\). Each \( \pi \in \Pi \) is a distribution over the set of assignments to some subset \( \pi \) of the RDP’s set of propositions, with one such distribution associated with each cluster. \( Tr : H \rightarrow \Pi \) maps each history in the sample to the distribution associated with its cluster.

To compare the models we define the following loss function:

\[
\text{loss} = - \sum_{h \in H} \log(P(h|Tr(h)) + \lambda \cdot \log(\sum_{\pi \in \Pi} |supp(\pi)|)
\]

(3)

\[
P(h|Tr(h)) = \prod_{i=1}^{n} P(o_i|o_1a_1 \ldots o_{i-1}a_{i-1}; Tr(h))
\]

(4)

Where \( |supp(\pi)| \) is the size of the support of distribution \( \pi \). Thus, our loss function is the log-likelihood of the data with a regularizer that penalizes models with many clusters, and models with “mega”-clusters with large support.

4.5 Generate a Mealy Machine and an MDP
We now use the flexfringe algorithm [Verwer and Hammer-schmidt, 2017] to learn a Mealy Machine from our data. With every trace in our original sample, we associate the index of the cluster it belongs to. The result is a Mealy Machine representing the RDP.

Let \( M_{Me} = (S_{Me}, o_{Me}, \Sigma, \Lambda, T, G) \) be the learned Mealy Machine. From this Mealy Machine we can generate an MDP.
We define two domains: Non Markovian Multi-Arm Bandit (MAB) and Rotating Maze. The original MAB is stateless. In our version transition probabilities depend on the history of success for each arm, making it a two states domain. The Maze problem is based on an agent navigating on a grid toward a designated location, while the orientation might change. For Mealy Machine learning we used the ESDM implementation from the FlexFringe library \cite{Verwer2017}. To solve the learned RDPs we use UCT, extended to RDPs, and compare it with a baseline of $R_{\text{Max}}$ \cite{Brafman2002} that uses the RDP states as its states, used as baseline. The results are displayed in Figure 1. We show the value of the optimal policy ($Optimal$), the quality of the policies learned by the above three algorithms at each evaluation step, and the average reward accumulated during learning by the first two algorithms. Each experiment was repeated five times. We plot the average over these five repetitions with error bars representing the std. To evaluate the quality of the current policy during the learning process, the optimal policy for the current model was computed online using UCT. 50 trials were conducted using the currently learned Mealy Machine. MAB trials were 10 steps long, and Maze trials were terminated after 15 steps if the goal was not reached. The graph shows the average (over 50 trials) per-step rewards of these policies (averaged over 5 trials), and the average (over 5 trials) accumulated reward obtained as S3M was sampling traces.

5.2 Results

For each domain we used three configurations: (1) Random Sampler: S3M with Pure Exploration sampling; (2) Smart Sampler: S3M with Smart Sampling; (3) RMax: The model-based RL algorithm $R_{\text{Max}}$ \cite{Brafman2002} that uses the RDP states as its states, used as baseline.

In our experiment we used 2 arms/actions for all of the three variations of the domain. The winning probabilities of the machines of the RotatingMAB were $(0.9, 0.2)$, for CheatMAB $(0.2, 0.2)$ and for MalfunctionMAB $(0.8, 0.2)$.

5.1 The Domains

We define two domains: Non Markovian Multi-Arm Bandit (MAB) and Rotating Maze. The original MAB is stateless. In our version transition probabilities depend on the history of success for each arm, making it a two states domain. The Maze problem is based on an agent navigating on a grid toward a designated location, while the orientation might change. For Mealy Machine learning we used the ESDM implementation from the FlexFringe library \cite{Verwer2017}. To solve the learned RDPs we use UCT, extended to RDPs, and compare it with a baseline of $R_{\text{Max}}$ – a model-based MDP learning algorithm \cite{Brafman2002}. This learning algorithm essentially assumes (wrongly) that the RDP transitions are Markovian.

Multi-Arm Bandit Domain

The Multi-Arm Bandit (MAB) is the simplest class of RL domains. Standard MAB is state-less – hence there are no transition function to learn. At each step the agent chooses one of $n$ actions, and receives a reward that depends (possibly stochastically) on the choice of action. Our Non-Markovian MAB extends this by making the probability of receiving a (fixed-size) reward depend on the entire history of previous actions. It is essentially a two-state RDP – where the state indicates whether a reward was received or not. We created three MAB-based RDP models:

1. RotatingMAB: Let $\pi$ be a vector that assigns the probability of winning the reward for each action. This probability shifts right (i.e., $+1 \bmod n$) every time the agent receives a reward. Therefore, the probability to win for each arm depends on the entire history, but via a regular function.
2. MalfunctionMAB: One of the arms is broken, s.t. after the corresponding action is performed $k$ times, its probability of winning drops to zero for one turn.
3. CheatMAB: There exists a sequence of actions s.t. after performing that sequence, all actions lead to a reward with probability 1 from that point on.
quickly, and the accumulated rewards increase steadily, while the random sampler does worse. This is especially pronounced in the Cheat MAB domain, which is the most complex domain. We believe the reason for the weak performance of random sampling in this domain is that too many of the samples are not along the more interesting traces that discover the “cheat” sequence. Therefore, it is more difficult for it to learn a good Mealy Machine that can exploit it. Surprisingly, in the Maze domain, unlike in the MAB domains, there is no significant difference between the two S3M versions. We hypothesize that in Maze, there is more to learn about the general behavior of transitions because there are more states, and the random sampler generates more diverse samples that provide a more accurate statistics on various states. The smart sampler, on the other hand, does not. Moreover, while the domain has more states, the regular expression that governs the dynamics is relatively simple, and so the random sampler is still able to learn the corresponding automaton.

Generally speaking, we see a high correlation between the quality of the samples collected by the sampler and the quality of the learned model: when the average reward of the samples is monotonically increasing so does the averaged reward of the policy obtained by MCTS. An open question is what is the exact relation: do samples that concentrate along desirable traces yield better Mealy Machines, or is it the case that because we learn a better Mealy Machine, the traces generated by the Smart Sampler have higher rewards (naturally).

6 Discussion and Summary

We presented the first algorithm for learning Regular Decision Processes. By viewing the RDP specification as a Mealy Machine, we were able to combine Mealy Machine and RL algorithms to obtain an algorithm for learning RDPs that quickly learns a good Mealy Machine representation in our experiments. Naturally, there is much room for improvement, especially in methods for better sampling and better aggregation of histories.
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