Planning with RL and episodic-memory behavioral priors

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Abstract—The practical application of learning agents requires sample efficient and interpretable algorithms. Learning from behavioral priors is a promising way to bootstrap agents with a better-than-random exploration policy or a safe-guard against the pitfalls of early learning. Existing solutions for imitation learning require a large number of expert demonstrations and rely on hard-to-interpret learning methods like Deep Q-learning. In this work we present a planning-based approach that can use these behavioral priors for effective exploration and learning in a reinforcement learning environment, and we demonstrate that curated exploration policies in the form of behavioral priors can help an agent learn faster.

Index Terms—Planning, Behavior Priors, Sample Efficient Learning, Reinforcement Learning.

I. INTRODUCTION

Reinforcement learning (RL) agents often struggle from cold start problems, especially in the case of long horizon tasks \[1\][2][3][4]. It arises due to random initialization of models leading to poor exploration and thus very little learning in initial phase of training.

To solve this problem, imitation learning \[5][6] algorithms introduce behavior priors. Expert demonstrations in the form of \textit{SARS}' tuples are provided to the agent prior to phase-III (RL) training. The agents thus starts with a knowledge of "good" or "safe" actions to take in most of the situations, leading to more effective exploration in the phase-III (RL) and hence better sample efficiency. As the agent explores, it gathers the missing knowledge for states not encountered in demonstrations, and eventually learns skills at par (and beyond) with the expert. A recent popular example of this approach is DQiD \[7]. Existing Q-Learning-based methods require large amounts of data to create robustness to low-level pixel noise and high-level feature noise. This coupled with dynamically changing environment \[8] make it complicated to use such networks for practical application. Moreover, the learned policies are not interpretable, leading to difficulty in validating such models.

In order to make learning more robust, discrete and interpretable \[9] we demonstrate our Planner module. It is loosely based on the Monte Carlo tree search \[10], which evaluates different alternatives from the current state, conditioned on different actions to a certain depth, and choose the best on the basis of expected reward.

II. EXPLORATION WITH BEHAVIORAL PRIORS

The learning starts with using an initial controller $C$ that executes the action given by behavior priors. Essentially, the
goal is to gather tuple sequences \((S, A, R, S', D)\) of variable length \(T\) returned by the environment, in order to learn value of states, given the initial controller \(C\), and initialize planning component which leads to more efficient exploration with priors in further phases of learning. For our experiments we focus on Learn-to-Race (L2R) environment [11][12][13], the details of the environment are given in Section IV. In L2R, we modelled the behavior prior as changing direction when an unsafe state is encountered. To determine if the state is safe/unsafe, we let the agent drive straight at a constant velocity until the episode ends. Due to curved tracks, this means that driving straight will always end in a negative reward due the car moving out of the track. For these episodes, we mark the last unsafe offset frames as unsafe and the remaining as safe states. The agent is trained in phased manner, starting from behavior prior, followed by RL phase (Phase-III). In behavior prior based phase-I the agent was trained to determine low value states as described above (also see Appendix, Algorithm [3], and in-phase II it explores actions in these low valued states (Algorithm [1]). To improve further and fill in the missing knowledge, we use planner (See Appendix, Algorithm [2]) to train the agent in RL phase (phase-III) as shown in Algorithm [2].

### III. Planning with episodic memory behavioral priors

#### A. State representation

We trained U-Net [14] and (Sigma) VAE [15] models on the collected pictures from the previous phases to translate visual representations into the latent space of the VAE. For encoding the states, instead of using RGB images returned from the environment, the algorithm encodes into latent dimensions the semantic masks of the road. The selection of the right semantic is important for performance [16] and is a design choice for different environments. For L2R, we selected the masks of road-track as the semantic information. However, other environments may require different encoding schemes.

Mathematically,

\[
E(O) = V(U(O))
\]

where \(E\) is the encoding of the observation \(O\). \(U\) is semantic extractor U-Net (\(F_{U\text{net}}\)) model. \(V\) is a sigma variational autoencoder (\(F_{V\text{VAE}}\)) to encode the semantic masks extracted by U-Net. The parameters of these models are provided in Appendix.

#### B. Episodic Memory

The agent estimates an expected reward value of states using trajectories collected with initial behavioral prior policy \(C\). We use low valued states as the primary candidates to explore actions, which leads to targeted exploration in the initial learning phase.

Episodic memory \(M\) consisting of \(N\) experienced trajectories, where \(S^a_n\) is state at time step \(a\) in the \(b^{th}\) trajectory, \(A^a_n\) is action, \(R^a_n\) is observed reward and \(I^a_n\) is any other auxiliary information are collected in the following form, each tuple is called a Trajectory Point (TP) \([(S^1_1, A^1_1, R^1_1, I^1_1), (S^2_2, A^2_2, R^2_2, I^2_2), \cdots (S^N_N, A^N_N, R^N_N, I^N_N)]\). Once stored, the planner \(P\) selects the best trajectory point \(TP_{best}\) from the episodic memory \(M\) based on criteria listed below and executes action taken from that trajectory for a given query state i.e \(P(M, S) = TP_{best} : \mathbb{E}(R|S, A)\) is maximized over all \(i\).

Apart from state-action-reward we also require other information like a pointer to the next TP in a trajectory and other convenience attributes like Grid coordinates (see Latent Grid), pointer to \(k\)-th step TP in future, step index and trajectory ID etc. for various update and retrieval tasks. For all algorithmic purposes, consider TP as a data structure which stores all the above values.

#### C. Latent Grid and Storing Trajectories

To reduce noise, artifacts and dimensionality of input observation space, we encode the observations into low dimensional space of dimensionality \(m\) (for L2R, \(m = 2\)) using the method described in section III-A. Since we aim to leverage searchability of states in this lower dimensional latent space, we quantize the latent into a grid \(L\) of size \(g\) (for L2R, it will be a 2 dimensional grid of size \(g = 100\times100\)). Each cell in the grid represents a range of continuous latent encoding depending on the range of values in the stored DB. Mathematically, to convert an encoding \((E : R^m)\) into latent grid coordinates \((G : N^m)\) of matrix with size \(g\), we use the formula \((E = \text{collection of all encoding value})\)

\[
G_i = \text{floor} \left( \frac{E_i}{(\max(E) - \min(E)) + g/2} \right) \quad \forall i \in [1 \cdot m]
\]

Effectively, each grid cell stores a list of all TPs that lie on it, and stores their average value as the its cell value for future use.

![Latent Grid population heatmap before and after Training](image)

As the agent explores the environment and visits each cell, the cell accumulates the value \(VC\) as the average of the sum of discounted future rewards for each TP lying on grid coordinate \(C\). Fig. 3 demonstrates how the cells are populated by explorations during training phases.

#### D. Retrieving Trajectory Points

In order to select the action to be taken, the planner takes as an input the last \(p\) states observed and the episodic memory stored in the latent grid and ranks the neighboring stored
trajectory points based on an estimate of best state values in their near future of \( k \) time steps.

The ideology of above design is as follows:

- **Searching with the correct context**: The Markov state model assumption that the future state only depends on the current is often violated in a practical application environment. We aim to alleviate some of this limitation by selecting that trajectory which is similar to the current at least for the past \( p \) states. The distance between two state encodings \( s^0_1 \) and \( s^0_2 \), both \( m \) dimensional, therefore is:

\[
\Delta(s^1, s^2) = \sum_p (||s^1_{-p} - s^2_{-p}||^2 + ||s^1_{-p+1} - s^2_{-p+1}||^2 + \cdots ||s^1_0 - s^2_0||^2) \tag{2}
\]

where \( s_n \) is state occurring \( n \) timesteps before \( s_0 \) and \( ||.||^2 \) is the L2 norm. This ensures that there is more correlation between the matches than mere visual similarity. This is important in environments where context plays a significant role and is not captured by state information alone.

- **Searching in a limited area**: While searching for a match in the latent space, we only consider points which are very close to query state. This avoids matches with high value states which do not correspond to the query state, and gives an indication to the planner to explore rather than exploit. We consider TPs which lie within \( n \) steps of 8-connected grid cells as close neighbors, for L2R we have set \( n = 1 \).

- **Criteria of selection of ideal TP**: For those states in immediate vicinity of current state, we only consider the value of those state in next \( k \) time steps. This is to ensure that following these points leads to high rewards.

The planner effectively explores when the best match is not a good values state, otherwise explores an action which is not yet explored in the region, a complete algorithm is given in Appendix Algorithm 3.

IV. EXPERIMENTS

To demonstrate the applicability of our approach we deploy our agent on L2R environment, the environment is Formula 1 style single player racing simulator, which provides first person view of the car as shown in the Fig. 1 and Fig. 2 along with velocity information. The action space have two actions Steering and Acceleration, both of which can be between \([-1 \ldots 1]\). It features realistic physics and visuals. The reward at every time step is proportional to the percentage of track completed in that time step and a penalty which is a large negative award associated with going out of the track with at least two wheels outside the road area. Our approach works with continuous action space as well as with discrete action space, something a lot of other approaches cannot provide. For the discrete action space, we have restricted steering exploration to only three values, that is \(-1\) (turn right), 0 (drive straight) and 1 (turn left). We trained the U-Net and VAE model using the observations collected in Phase-I, with VAE finetuning in Phase-III (RL) as well.

See Fig. 4 for training curves for VAE.

The latent space shows good separation between visually distinct scenes as shown in Fig. 2. The performance metrics and comparisons are shared in Fig 3, Fig 4 and Table I.

We have presented results of various agents which were trained on a seen track in L2R environment, and evaluated for 3 laps on unseen track. We have also included Human (Expert), Random agent and a Model Predictive Controller baselines for comparison. The MPC model follows a center line of the track at moderate speed and is treated as a naive policy for the task. The metrics we have chosen for our study are: success rate, which is an indicator of how much % of the track an agent could complete without failing and average...
speed, reported as distance covered per unit time (KM/H). See Appendix, Algorithm 5 for evaluation algorithm.

Table 1 shows the comparison with the above baselines, along with another popular deep learning approach Soft Actor Critic. The Soft Actor Critic required 48 hours of training, compared to 2 hours of training for our algorithm (incl. behavior priors, training of VAE, U-Net and Phase-III (RL)) on a NVIDIA GTX 1660Ti GPU, a training time interaction

![Comparison of nearest states with different executed actions.](image)

![Success Rate graph for RL training phase (Phase-III).](image)
V. DISCUSSION

We presented a behavior prior initialized agent outperforming SAC on L2R task with substantially less learning interactions with the environment. The planner module utilizes stored episodic memory to learn value estimates and guide the agent towards efficient exploration. The approach enables sample efficient adaptation and a few-shot learning policy [17]. We have shown with our results that a planning approach, combined with behavior priors assessments, can enable a sample efficient few-shot learning and provide interpreted agent decisions.

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Algorithm 3 Planner Algorithm for Selecting Action

**Input:** Latent Grid $L$, Query state along with $p$-1 past states $E_{q}$, Maximum distance to qualify as a neighbor $n$, Maximum neighbors to select for sorting $q$, Value function lookahead range $k$, Minimum threshold value of state to be considered as good state to follow $val_{thresh}$

**Output:** Action to execute

1. $g_{nn} \leftarrow$ neighbors($L, E_{q}, n, q$) ▷ For all neighbors lying in $\pm n$ grid coordinate as $E_{q}$, return top $q$ ($q=10$) neighbors which are closest to $E$ according to the sum of $p$ ($p=3$ history size) element wise L2 distance as described above
2. $best \leftarrow$ sort(ngrid_max($g_{nn}, k$)) ▷ Sort TPs in $g_{nn}$ by the maximum value estimate in max($t, t+k$) timesteps ($k=10$)
3. **if** best $= \phi$ OR best[0].ngrid_max $< val_{thresh}$: **then** ▷ If the value of best neighbor is not min(10%), then increase the search to the entire latent grid. This is guaranteed to yield a positive match, but can be a poor match and slower.
   4. $g_{nn} \leftarrow$ neighbors($L, E_{q}, \infty$)
   5. $best \leftarrow$ sort(ngrid_max($g_{nn}, k$))
   6. **end if**
7. action $\leftarrow$ best[0] action ▷ Copy the action of the best match
8. **return** action

Algorithm 4 Collection of trajectories with the initial controller $C$

**Input:** No. of episodes to explore $e$ ($=20$), Controller $C$, Environment $env$, Database $DB$ ($= \phi$), Gamma $g$, Unsafe offset $unsafe_{offset}$

**Output:** Trajectories

1. **for** $i = 0$ to $e - 1$ **do** ▷ LOOP for each episodes
2: done $\leftarrow$ false ▷ Explore till the episode ends
3: step $\leftarrow$ 0
4: ep_data $\leftarrow$ $\phi$
5: **while** not done **do** ▷ Query Controller for a naive exploration (behavioral prior)
6: step += 1
7: Sample action $a \leftarrow C$
8: obs, reward, done $\leftarrow env.step(a)$
9: ep_data $\leftarrow$ ep_data $\cup$ [obs, reward, i, step, done]
10: **end while**
11: ep_data $\leftarrow$ augment(ep_data, $g$, unsafe_offset) ▷ Compute and store future discounted rewards, mark last unsafe_offset frames of each episodes as unsafe
12: $DB \leftarrow DB \cup$ ep_data
13: **end for**
14: **return** $DB$
Algorithm 5 Agent Evaluation

Input: Trained latent Grid $L$, No. of previous state to match trajectories $p$, Maximum distance to qualify as a neighbor $n$, Maximum neighbors to select for sorting $q$, Value function lookahead range $k$, U-Net $Un$, VAE $vae$, Environment $env$

Initialization
1: $E \leftarrow Deque(\text{MAX}_LEN = p)$ \hspace{1cm} \triangleright [E_{-p}, E_{-p+1}, ..., E_0]$
2: $obs \leftarrow env.reset()$

Evaluate
3: for $i = 0$ to $p$ do
4: \quad $E.append(Vae(\ Un(\ obs\ )))$
5: end for
6: best $\leftarrow$ None \hspace{1cm} \triangleright Check if best is one of $D_n$ nearest neighbors of $E_p$
7: for $step = 0$ to $\infty$ do
8: \quad $g_{nn} \leftarrow neighbors(L, E, n, q)$ \hspace{1cm} \triangleright For all neighbors lying in $\pm n$ grid coordinate as $E_0$, return top $q$ ($q=10$) nearest neighbors which are closest to $E$ according to the sum of $p$ ($p=3$ history size) element wise $L2$ distance
9: \quad best $\leftarrow$ sort(ngrid_max($g_{nn}, k$)) \hspace{1cm} \triangleright Sort TPs in $g_{nn}$ by the maximum value estimate in max($t, t+k$) timesteps ($k=10$)
10: if length(best) $= 0$ OR best[0].ngrid_max $< 0$ then \hspace{1cm} \triangleright If the value of best neighbor is not $> \min(10\%)$, then increase the search to the entire latent grid. This is guaranteed to yield a positive match, but can be a poor match and slower.
11: \quad $g_{nn} \leftarrow neighbors(L, [GX,GY], \infty)$
12: \quad best $\leftarrow$ sort(ngrid_max($g_{nn}, k$))
13: end if
14: action $\leftarrow$ best[0].action
15: $obs, reward \leftarrow env.take\_action(action)$
16: $e \leftarrow Vae(\ Un(\ obs\ ))$ \hspace{1cm} \triangleright Convert observation to encoding
17: $E.append(e)$
18: Store($obs, action, reward, step$)
19: end for

A. Model Training

1) U-Net: We collected image masks from the environment during the Phase-I-Straight Driving (around 600 image-mask pairs) and applied Brightness (0.2), Contrast (0.2), Color Jitter (0.2), Hue(0.2), Flip (0.5), Scale (min = 0, max = 0.2) and Rotation (min = 0, max = 0.3) transformation for data augmentation. The architecture is as described in [14] with input image size = 64 x 64 We trained the model for 60 epochs, with lr = 0.0001 without any LR scheduling. We used Adam Optimizer for our experiment.

2) VAE: We collected image masks from the environment during the Phase-I training (around 600 images) The architecture is as described in [15] with input image size = 28 x 28 and $z_{dim} = 2$. We trained the model for 150 epochs, with lr = 0.001 without any LR scheduling. We used Adam Optimizer for our experiment.

B. Planner

For Learn2Race [11] environment we have used the following parameters for our planner: Past states to consider for matching TP $p = 3$, Maximum distance to qualify as a neighbor $n = 1$, Maximum neighbors to select for sorting $q = 10$, Value function lookahead range $k = 10$, Minimum threshold value of state to be considered as good state to follow $val_{thresh} = 0$