Learning-Driven Exploration for Reinforcement Learning

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Abstract. Deep reinforcement learning algorithms have been shown to learn complex skills using only high-dimensional observations and scalar reward. Effective and intelligent exploration still remains an unresolved problem for reinforcement learning. Most contemporary reinforcement learning relies on simple heuristic strategies such as $\epsilon$-greedy exploration or adding Gaussian noise to actions. These heuristics, however, are unable to intelligently distinguish the well explored and the unexplored regions of the state space, which can lead to inefficient use of training time. We introduce entropy-based exploration (EBE) that enables an agent to explore efficiently the unexplored regions of the state space. EBE quantifies the agent’s learning in a state using merely state dependent action values and adaptively explores the state space, i.e. more exploration for the unexplored region of the state space. We perform experiments on many environments including a simple linear environment, a simpler version of the breakout game and multiple first person shooter (FPS) games of VizDoom platform. We demonstrate that EBE enables efficient exploration that ultimately results in faster learning without having to tune hyperparameters.

Keywords: Reinforcement Learning · Exploration · Entropy.

1 Introduction

Reinforcement learning (RL) is a sub-field of machine learning where an agent interacts with an environment of unknown dynamics. The objective of any RL algorithm is to learn a policy that maximizes the cumulative reward obtained by the agent. Since the agent does not begin with perfect knowledge of the environment dynamics, it has to learn solving the task through trials and errors. This gives rise to fundamental trade-off between exploration vs exploitation. Exploration is the process in which the agent learns novel information about the environment, typically through reducing its uncertainty about attainable rewards and the environment dynamics. The new knowledge acquired through exploration may offer long-term gains. In exploitation, on the other hand, the agent maximizes its reward using the knowledge it already has about the environment. A long-standing problem in RL is to find ways to achieve better trade-off between exploration and exploitation.
In this work, we argue that state dependent action values can provide valuable information to the agent about its learning progress in a state. We use the concept of entropy from information theory to quantify agent’s learning in a state and subsequently make decision whether to explore in a state based on it. This minimizes the prospects of unnecessary exploration while still exploring the poorly explored regions of the state space.

2 Related Work

Existing entropy-based exploration strategies can be broadly divided into two categories [1]: entropy regularization for RL and maximum entropy principle for RL. Entropy regularization attempts to alleviate the problem of premature convergence in policy search by imposing the information-theoretic constraints on the learning process. In [2], authors constrain the relative entropy between old and new state-action distributions. Some recent works including [3,4] alleviate this problem by bounding the KL-divergence between the current and old policies. Maximum entropy principle methods for RL aim to encourage exploration by optimizing a maximum entropy objective. Authors in [5,6] construct this objective by simply augmenting the conventional RL objective with entropy of the policy. [7,8] used maximum entropy principle to make MDPs linearly solvable while [9] employed maximum entropy principle to incorporate prior knowledge into RL setting.

Our proposed method belongs to the class of methods that use quantification of uncertainty for exploration. [10] view the problem of exploration from an information-theoretic prospective and maximizes the information that the most recent state-action pair carries about the future. [11], on the other hand, introduced an exploration strategy based on maximization of information gain about the agent’s belief of the environment dynamics. Using information gain for exploration can be traced to [12] and has been further explored in [13,10,14].

Practical reinforcement learning algorithms often utilize simple exploration heuristics, such as $\epsilon$-greedy and Boltzmann exploration [15]. These methods, however, exhibit random exploratory behavior, which can lead to exponential regret even in the case of simple MDPs.

Another class of exploration methods focus on predicting the environment dynamics [16,17,18,19]. Prediction error is used as a basis of exploration and the prediction error tends to decrease as the agent collects more information similar to the current one about the environment dynamics. These methods, however, tend to suffer from the noisy TV problem [19] in stochastic and partially-observable MDPs. [19] introduced the so-called internal curiosity module to mitigate the noisy TV problem where the focus is on predicting only those environmental features that are relevant to the agent’s decision making.

Our proposed method differs from entropy regularization and maximum entropy principle methods for RL in the sense that we use entropy to quantify agent’s learning progress in a state. Unlike imposing entropy constraints on old and new policies in entropy regularization methods, we use entropy to decide
the need for exploration in a state. Still we focus on optimizing the conventional RL objective unlike maximum entropy principle methods where the optimizable objective is altered to improve the exploratory behavior of the agent. This allows the agent to learn policies that obtain maximum rewards without imposing constraints on the learning process.

3 Preliminaries

3.1 Reinforcement Learning

Reinforcement learning is a sequential decision making process in which an agent interacts with an environment $E$ over discrete time steps; see [15] for an introduction. While in state $s_t$ at time step $t$, the agent chooses an action $a_t$ from a discrete set of possible actions i.e. $a_t \in \mathcal{A} = \{1, \ldots, |\mathcal{A}|\}$ following a policy $\pi(s)$ and gets feedback in form of a scalar called reward $r_t$ following a scalar reward function, $r : S \times \mathcal{A} \to \mathbb{R}$. As a result, the environment transitions into next state $s_{t+1}$ according to transition probability distribution $\mathcal{P}$. We denote $\gamma \in (0, 1]$ as discount factor and $\rho_0$ as initial state distribution.

The goal of any RL algorithm is to maximize the expected discounted return $R_t = \mathbb{E}_{\pi, \mathcal{P}}[\sum_{\tau=t}^{\infty} \gamma^{\tau-t}r_\tau]$ over a policy $\pi$. The policy $\pi$ gives a distribution over actions in a state.

Following a stochastic policy $\pi$, the state dependent action value function and the state value function are defined as

$$Q^\pi(s, a) = \mathbb{E}[R_t | s_t = s, a_t = a, \pi],$$

$$V^\pi(s) = \mathbb{E}_{a \sim \pi(s)}[Q^\pi(s, a)].$$

3.2 Deep Q-Networks in Reinforcement Learning

To approximate high-dimensional action value function given in preceding section, we can use deep Q-network (DQN): $Q(s, a; \theta)$ with trainable parameters $\theta$. To train this network, we minimize the expected squared error between the target $y_t^{DQN} = r + \gamma \max_b Q(s', b; \theta^-)$ and the current network prediction $Q(s, a; \theta_i)$ at iteration $i$. The loss function to minimize is given as

$$L_i(\theta_i) = \mathbb{E}[(Q(s, a; \theta_i) - y_t^{DQN})^2],$$

where $\theta^-$ represents the parameters of a separate target network that greatly improves the stability of the algorithm as shown in [20]. Please see [21] for a formal introduction to deep neural networks.

3.3 Entropy

Let us have a discrete random variable $X$. A discrete random variable $X$ is completely defined by the set $\mathcal{X}$ of values that it takes and its probability
distribution \( \{p_X(x)\}_{x \in \mathcal{X}} \). Here we assume that \( \mathcal{X} \) is a finite set, thus the random variable \( X \) can only have finite realizations. The value \( p_X(x) \) is the probability that the random variable takes the value \( x \). The probability distribution \( p_X : \mathcal{X} \to [0, 1] \) must satisfy the following condition

\[
\sum_{x \in \mathcal{X}} p_X(x) = 1.
\]

The entropy \( H_X \) of a discrete random variable \( X \) with probability distribution \( p_X(x) \) is defined as

\[
H_X = - \sum_{x \in \mathcal{X}} p_X(x) \log_b p_X(x)
\]

\[
= -\mathbb{E}_{X \sim p_X} [\log_b p_X(x)],
\]

where the logarithm is taken to the base \( b \) and we define by continuity that \( 0 \log_b 0 = 0 \).

Intuitively, entropy quantifies the uncertainty associated with a random variable. The greater the entropy, the greater is the surprise associated with realization of a random variable.

4 Entropy-Based Exploration (EBE)

In this section, we explain the proposed entropy-based exploration (EBE) method. First we go through the motivation behind EBE and then we present the mathematical realization for the concept.
4.1 Motivation

Usually in RL training, the agent has gathered more knowledge in well explored region of the state space. The lack of knowledge in unexplored states is a result of insufficient learning in those states. Therefore, an effective exploration strategy should adapt itself to explore more in states where the agent has performed less learning, which we refer to as learning-driven exploration. Learning-driven exploration enables the agent to perform more exploration in poorly explored regions of state space, which usually occur at the later stages of training episode. This allows the agent to explore deeper into the state space resulting into deep exploration. Our definition of deep exploration is different from [22] where deep exploration means “exploration which is directed over multiple time steps or far-sighted exploration” [22]. In our work, Deep exploration concerns spatially extended exploration in the state space. The concept is illustrated in Figure 2.

As the training process continues, the well explored region of the state space increases. Figure 2 shows two different training trajectories, related to EBE and $\epsilon$-greedy exploration, at three different instances in the presumed learning process. The redness of a trajectory indicates the exploration probability in that state. For EBE, the exploration probability is small in well explored region of the state space and it increases as we get closer to unexplored region. This enables the agent to explore adaptively based on its learning in a state, resulting in deep exploration. But for $\epsilon$-greedy exploration where value of $\epsilon$ is annealed from the start to the end of the training process, at a particular instant in learning process, the agent explores in all states with the same probability irrespective of its learning in those states. Adaptive exploration by EBE enables the agent to allocate more resources towards exploring poorly understood regions of the state space, thus improving the learning progress.

1 word deep is used here in different context from deep learning.
4.2 Entropy-Based Exploration (EBE): A Realization of Learning-Driven Deep Exploration

The agent quantifies the utility of an action in a state in the form of state dependent $Q$-values. We can use the difference between $Q$-values in a state as an estimate of agent’s learning progress in that state. Therefore, we use $Q$-values to define a probability distribution over actions in a state, i.e.

$$p_s(a) = \frac{e^{Q(s,a)}}{\sum_{b \in A} e^{Q(s,b)}},$$  \hspace{1cm} (1)

where $A$ is the set of all possible actions in state $s$. Here we note that $e^{Q(s,a)}$ may cause numerical overflow when $Q(s,a)$ is large. To improve numerical stability, we use the so-called max trick. We thus have

$$p_s(a) = \frac{e^{Q(s,a) - Q_\alpha(s)}}{\sum_{b \in A} e^{Q(s,b) - Q_\alpha(s)}},$$  \hspace{1cm} (2)

where $Q_\alpha(s) = \max_{\tilde{a} \in A} Q(s, \tilde{a})$. This improves the numerical stability while keeping the distribution $p_s(a)$ unchanged. We then use $p_s(a)$ to obtain state dependent entropy, $\tilde{H}(s)$, as follows

$$\tilde{H}(s) = -\sum_{a \in A} p_s(a) \log_b p_s(a),$$  \hspace{1cm} (3)

where $b > 0$ is the base of logarithm. We note that $\tilde{H}(s)$ may be greater than 1 when $|A| > b$, therefore, we normalize $H(s)$ between 0 and 1. Since maximum value the entropy can take is $\log_b(|A|)$, we define a scaled entropy $H(s) \in [0,1]$ as follows:

$$H(s) = -\frac{\sum_{a \in A} p_s(a) \log_b p_s(a)}{\log_b(|A|)} = -\frac{\sum_{a \in A} p_s(a) \log_2 p_s(a)}{\log_2(|A|)}.$$  \hspace{1cm} (4)

$H(s)$ in equation (4) quantifies the agent’s learning in state $s$: the lower the entropy $H(s)$, the more learned the agent is that some actions are better than others. Therefore, we use $H(s)$ to guide exploration in a state: greater the value of $H(s)$, more is the need for exploration. Given $H(s)$ in a state from equation (4), the agent explores with probability $H(s)$ i.e. it behaves randomly. In practice, entropy-based exploration is similar to $\epsilon$-greedy exploration method with $\epsilon$ replaced with state dependent $H(s)$.

**How does entropy estimate agent’s learning in a state?** To see how entropy can estimate agent’s learning in a state, we see that state space can be broadly classified into two categories: states in which choice of action is crucial and states in which choice of action does not significantly impact what happens
in the future. For later states, some actions are decisively better than others. Quantitatively, it means that $Q$-values for better actions are significantly higher than $Q$-values of the remaining actions. Therefore, the distribution defined in equation (2) is highly skewed towards better actions and by equation (4), the entropy of these states is low. Note that the lowest achievable entropy may be different for different states.

Consider, for example, the case where the agent is trained to play VizDoom game Seek and Destroy. The details about the environment and experimental setup are given in Section 5.3. We consider three cases comprised of an untrained agent, a partially trained agent and a trained agent. Here, we define $H_o \in [0, 1]$ as entropy averaged over an entire episode, i.e.

$$H_o = \frac{1}{N} \sum_{i=1}^{N} H(s_i),$$

where $N$ is the number of steps in the episode, $s_i$ represents state at $i^{th}$ step and $H(s_i)$ gives entropy of $s_i$ as defined in equation (4). We test the agents for 10 consecutive episodes. Figure 1 plots $H_o$ and accumulated episode reward versus test episodes. We see in Figure (a) that $H_o$ is lowest for trained agent for all episodes. Also the trained agent obtains the highest accumulative reward in all episodes as shown in (b). The partially trained agent still has significant $H_o$ values for all episodes which reflects its incomplete learning.

These results show that entropy is a good measure to estimate agent’s learning in a state, which in turn can be used to quantify the need for exploration. This forms the base for our proposed entropy-based exploration strategy.

It is worthwhile to note that for states where all available actions have similar $Q$-values, the entropy remains close to 1 irrespective of learning progress. Therefore, entropy does not reflect the agent’s learning in these states. This, however, does not affect the learning process as choice of action is practically irrelevant in these states owing to similar $Q$-values as mirrored by experiments in Section 5.

5 Experiments

We demonstrate the performance of EBE on many environments including a linear environment, a simpler breakout game and multiple FPS games of Vizdoom [25]. Results shown are averaged over five runs. Please note that all appendices are placed in supplementary material due to limited space. Code to reproduce the experiments is given at: https://github.com/Usama1002/EBE-Exploration.

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2 the $Q$-network was initialized using Kaiming Uniform method and no further training was performed.

3 the agent was trained using EBE for two epochs only.

4 the agent was trained using EBE for 20 epochs.
5.1 Value Iteration on Simple Linear Environment

We start our experiments by measuring the performance of EBE on a simple value iteration task. The reason for choosing this task is that it is devoid of many confounding complexities and provides better insight into used methods. Moreover, exact optimal $Q$-values, $Q^\ast(s, a)$ for all $(s, a) \in (S \times A)$, can be computed analytically which helps monitor the learning progress.

The environment is described in Figure 3(a). We use temporal difference based tabular Q-learning without eligibility traces to learn the optimal $Q$-values, $Q(s, a)$ for all $(s, a) \in (S \times A)$.

As baselines, we use $\epsilon$-greedy exploration where $\epsilon$ value is linearly annealed from 1.0 to 0.0 over the number of episodes and Boltzmann exploration where the temperature is linearly decreased from 0.8 to 0.1. Agents are trained for 200 episodes with maximum episode length of 50 steps. Optimal steps to successfully reaching a rewarding state are 10. Values for discount factor and learning rate are 0.9 and 0.2 respectively. The evaluation metric is mean squared error between the actual $Q$-values, $Q^\ast(s, a)$, and the learned $Q$-values, $Q(s, a)$:

$$L = \sum_{s \in S, a \in A} (Q^\ast(s, a) - Q(s, a))^2.$$  

The squared error is plotted in Figure 3(b). We see that $Q$-values learnt with EBE converge to optimal $Q$-values while others fail. This is a very promising result as it indicates the ability of EBE to adequately explore the state space.

5.2 A Simpler Breakout Game

We experiment with a simpler breakout game whose state space is much simpler than that of Breakout game of Atari suite that allows detailed analysis of employed
methods, yet it is complex enough to offer significant learning challenge as it uses a neural network as function approximator and works on raw images as states. There are 15 bricks to break and the agent is rewarded 1 point for breaking each brick. Episode ends when one of the following happens: all bricks are broken, the paddle misses the ball or the maximum steps limit has reached. We use a stack of 2 images, the current image and the previous images, as our state observation. In any state, the agent can either move the paddle left, move it right or leave it still. EBE is compared to $\epsilon$-greedy exploration in which $\epsilon$ is linearly annealed from 1.0 to 0.0 over the number of episodes and Boltzmann exploration where temperature is linearly annealed from 1.0 to 0.01 over training process. Please see Appendix A for details regarding the experimental setup.

The results are shown in Figure 4. We see that agent trained with EBE learns much faster than those trained with $\epsilon$-greedy and Boltzmann exploration strategies, as shown in Figure 4(a). Figure 4(b) plots the training episode rewards versus the episode numbers. We see that for EBE, the agent starts performing high reward training episodes from the very start of training process, while training episode rewards for the agents trained with $\epsilon$-greedy and Boltzmann exploration increase steadily. This validates our hypothesis of deep exploration, in which the agent transitions quickly into the poorly explored region of the state space, which usually corresponds to the later states of a training episode.

5.3 VizDoom

We use VizDoom platform [25] to conduct experiments and compare EBE with $\epsilon$-greedy exploration.

Seek and Destroy The environment consists of grey walls, ceiling and floor. The agent is placed in the center of wall and a monster is spawned randomly on
Fig. 5. Performance of agents trained with entropy-based exploration (EBE), Boltzmann exploration and $\epsilon$-greedy exploration strategy on VizDoom game Seek and Destroy. (a) plots mean test score of 100 test episode scores played after each training epoch while (b) plots mean score of all training episodes played in a training epoch.

The agent is tasked to kill the monster with its gun. The gun can only fire straight, so the agent must come in line with the monster before firing a shot. Reward of 101 points is given for killing the monster. Penalty of 5 points is given for each missed shot, therefore optimal agent should kill the monster with only one shot. Penalty of 1 point is given for each step taken to motivate the agent to kill the monster faster.

The state space is partially observable to the agent via raw images. The agent can either move left, move right or attack in a state. The episode ends when either of the following happens: the monster is dead, player is dead or 300 time steps have passed.

We compare EBE with Boltzmann and $\epsilon$-greedy exploration strategies. In Boltzmann exploration, the temperature parameter is linearly annealed from 1.0 to 0.01 over the training epochs. For $\epsilon$-greedy exploration, $\epsilon$ is set to 1.0 for first epoch, then $\epsilon$ is linearly annealed to 0.01 till epoch 6. Thereafter, $\epsilon = 0.01$ is used. Please see Appendix A for further details about the training setup.

The results are shown in Figure 5. Mean test scores in Figure 5(a) show that agent trained with EBE outperforms the agents trained with Boltzmann and $\epsilon$-greedy exploration. Similarly, we see in Figure 5(b) that EBE exploration results in high reward training episodes considerably earlier in training that manifests deep exploration as defined in Section 4.1.

Defend the Center This environment consists of a circular map in which the agent is placed in the middle and monsters are spawned around it. To stay alive, the agent has to kill the monsters around it. The player can only rotate about its position. The player is rewarded one point for each kill and penalized one point for being killed. The agent is provided with 26 ammo, so it should learn to use the ammunition wisely to kill as many monsters as possible before being dead itself.
Table 1. Variants of baseline $\epsilon$-greedy exploration strategy.

| variant         | details                                                                 |
|-----------------|-------------------------------------------------------------------------|
| $\epsilon$-greedy I | $\epsilon = 1.0$ is used for first 100 epochs, then it is linearly annealed to 0.01 till 600 epochs. Afterwards $\epsilon = 0.01$ is used. |
| $\epsilon$-greedy II | $\epsilon$ is linearly annealed from 1.0 to 0.01 over the entire training process. |
| $\epsilon$-greedy III | $\epsilon = 1.0$ is used for first 100 epochs. $\epsilon$ is then linearly annealed from 1.0 to 0.01 over the remaining training process. |

Fig. 6. Plot of (a) mean test reward and (b) mean training reward per episode of agents trained with EBE, $\epsilon$-greedy and Boltzmann exploration strategies on VizDoom game Defend the Center. Plots show smoothed data while unsmoothed data is ghosted in the background. Smoothing method is adopted from [26] with weight 0.975.

The episode ends when the agent is dead or 2100 steps (60 seconds) have passed. The agent observes the state using raw frames and can either attack, turn left and turn right in a state. An episode is considered successful if the agent kills at least 11 monsters before being dead itself, i.e. score at least 10 points.

We compare EBE with $\epsilon$-greedy and Boltzmann exploration. We use three different variants of $\epsilon$-greedy exploration which are detailed in Table 1. For Boltzmann exploration, the temperature parameter is linearly annealed from 1.0 to 0.01 over the learning process. The agents are trained for 1000 epochs and each epoch consists of 5000 steps. 100 consecutive test episodes are played after each epoch. Details about the experimental setup are given in Appendix A.

The experimental results are shown in Figure 6 where (a) plots mean test rewards obtained by taking the mean of 100 test episodes after each epoch and (b) plots mean training reward obtained by taking the mean of all training episode rewards in an epoch. We see in Figure 6(a) that agent trained with EBE exploration attains the maximum mean test reward per episode after about 60% of training epochs as compared to other exploration strategies. Moreover, Figure 6(b) shows deep exploration, defined in Section 4.1, where EBE was able to perform high reward training episodes early on in the training process. This
result shows effectiveness of EBE on high-dimensional RL task that enables effective exploration without having to tune any hyperparameters.

**Defend the Line** This environment is similar to *defend the center* except that the map is rectangular with the agent placed on one side and monsters spawning on the opposite wall. The agent is rewarded one point for each kill and penalized one point for being dead. Here, the agent is provided with unlimited ammunition and limited health that decreases with each attack the agent takes from the monsters. The agent observes raw frames and can attack, turn left or turn right in a state. The episode ends when the agent is dead or episode times out with 2100 steps (60 seconds). The goal is to kill at least 16 monsters before the agent dies, i.e. to obtain at least 15 points in one episode. EBE is compared to the same baselines as considered in Section 5.3. Details about the experimental setup are given in Appendix A.

The experimental results are shown in Figure 7 where, similar to Figure 6, (a) plots mean test rewards per episode and (b) plots mean training reward per episode. Figure 7(a) that agent trained with EBE exploration attains the maximum mean test reward per episode after about 30% of training epochs as compared to other exploration strategies. Moreover, Figure 7(b) shows deep exploration, defined in Section 4.1, where EBE was able to perform high reward training episodes early on in the training process. This result shows that EBE performs effective exploration on high-dimensional RL tasks without having to tune any hyperparameters.

5.4 Comparison of EBE with Count-Based Exploration Methods

Some of the classic and theoretically-justified exploration methods are based on counting state-action visitations and turning this count into a bonus reward to
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Fig. 8. (a) Comparison of EBE with UCB and MBIE-EB on linear environment. (b) Comparison of EBE with #Exploration and pseudo-count based exploration on VizDoom game Seek and Destroy.

guide exploration. In the bandit setting, the widely-known Upper-Confidence-Bound (UCB) \cite{27} chooses the action \( a_t \) that maximizes \( \hat{r}(a_t) + \sqrt{\frac{2 \log t}{N(a_t)}} \) where \( \hat{r}(a_t) \) is the estimated reward of executing \( a_t \) and \( N(a_t) \) is the number of times the action \( a_t \) was previously chosen. Similar algorithms have been proposed for MDP setting that favor the selection of less visited state-action pairs by selecting the action \( a_t \) at time \( t \) that maximizes \( \hat{c}(s_t, a_t) = Q(s_t, a_t) + B(N(s_t, a_t)) \) where \( N(s_t, a_t) \) is the number of times the pair \((s_t, a_t)\) was previously visited. Here, \( B(N(s_t, a_t)) \) is the exploration bonus that decreases with the increase in \( N(s_t, a_t) \). Model Based Interval Estimation-Exploration Bonus (MBIE-EB) \cite{28} proposed using exploration bonus of the form \( B(N(s_t, a_t)) = \frac{\beta}{\sqrt{N(s_t, a_t)}} \), where \( \beta \) is a constant. Analogous to UCB for bandit-setting, we can get exploration bonus \( B(N(s_t, a_t)) = \sqrt{\frac{2 \log t}{N(s_t, a_t)}} \) for MDPs. We compare our proposed method EBE with UCB and MBIE-EB on linear MDP environment considered previously in Section 5.1 under the same experiments settings. As shown in Figure 8(a), EBE performs better than UCB in terms of convergence. The performance of MBIE-EB improves as value of \( \beta \) is increased and with \( \beta = 100 \), the performance of MBIE-EB becomes comparable to EBE.

MBIE-EB, UCB and related algorithms assume that the MDP is solved analytically at each timestep, which is only practical for small finite state spaces. Therefore, counting-based methods cannot be extended to high-dimensional, continuous state spaces as visit counts are not directly useful in large domains, where states are rarely visited more than once. \cite{29} addressed this issue by deriving pseudo-counts from arbitrary density models over the state space and allow generalization of count-based exploration algorithms to the non-tabular case. #Exploration algorithm \cite{30} uses hashing to discretize the high-dimensional state space whereby the states are mapped to hash codes which allows to count their visitations using a hash table. This visitation count is then used to compute the exploration bonus using the classic count-based exploration theory.
We compare EBE with pseudo-count based exploration algorithm [29] and #Exploration [30]. Please see Appendix B for implementation details of these baselines. Figure 8(b) shows the results for VizDoom game Seek and Destroy. EBE and #Exploration are able to learn solving the task with EBE learning much earlier while pseudo-count algorithm failed to solve the task. Similarly, Figure 9(a) and Figure 9(b) show comparison results for defend the center and defend the line, respectively. For both games defend the center and defend the line, EBE depicts efficient exploration by learning to solve the tasks with higher rewards much earlier than the baselines. However, #Exploration strategy settles at much lower score for both the games. Table 2 provides the wall time averaged across all runs for the considered exploration strategies for DTC and DTL. \( \epsilon \)-greedy is the most efficient in terms of wall time, followed by EBE. The exceptionally higher wall time required for #Exploration strategy can be explained by the online training of the autoencoder used for generating the hash codes.

Table 2. Wall time in hours averaged across five runs for various exploration strategies.

| environment     | EBE  | \( \epsilon \)-greedy | Boltzmann | #Exploration | pseudo-count |
|-----------------|------|------------------------|-----------|--------------|--------------|
| defend the center | 39   | 38                     | 42.5      | 64           | 51.5         |
| defend the line  | 40   | 38                     | 44        | 61.5         | 52           |

In conclusion, the proposed entropy-based exploration (EBE) method is able to achieve remarkable performance on tabular as well as on high-dimensional environments including various VizDoom games and a simpler breakout game. EBE is also efficient in terms of wall time and performs comparable to \( \epsilon \)-greedy exploration.
6 Conclusion

We have introduced a simple to implement yet effective exploration strategy that intelligently explores the state space based on agent’s learning. We show that entropy of state dependent action values can be used to estimate agent’s learning for a set of states. Based on agent’s learning, the proposed entropy-based exploration (EBE) is able to decipher the need for exploration in a state, thus, exploring more the unexplored region of state space. This results into what we call deep exploration which is confirmed by multiple experiments on diverse platforms. As shown by the experiments, EBE results into faster and better learning on tabular and high-dimensional state space platforms without having to tune any hyperparameters.

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