Stay Alive with Many Options: 
A Reinforcement Learning Approach for Autonomous Navigation

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Abstract

Hierarchical reinforcement learning approaches learn policies based on hierarchical decision structures. However, training such methods in practice may lead to poor generalization, with either sub-policies executing actions for too few time steps or devolving into a single policy altogether. In our work, we introduce an alternative approach to sequentially learn such skills without using an overarching hierarchical policy, in the context of environments in which an objective of the agent is to prolong the episode for as long as possible, or in other words ‘stay alive’. We demonstrate the utility of our approach in a simulated 3D navigation environment which we have built. We show that our method outperforms prior methods such as Soft Actor Critic and Soft Option Critic on our environment, as well as the Atari River Raid environment.

1. Introduction

Deep Reinforcement Learning in the past decade achieved unprecedented success in multiple domains ranging from playing simple Atari games (Mnih et al., 2013) to learning complex strategies and defeating pro players in Starcraft (Vinyals et al., 2017) and Go (Silver et al., 2017). However, the problem of learning meaningful skills in reinforcement learning remains an open question. The options framework (Sutton et al., 1999) provides a method to automatically extract temporally extended skills from a long horizon task with the use of options. Options are sub-policies that can be leveraged by some other policy in a hierarchical manner. The process of learning such temporal abstractions has been widely studied in the broad domain of hierarchical reinforcement learning (Flet-Berliac, 2019). In this paper, as the main contribution, we provide an alternate approach for learning options sequentially without a higher-level policy.

In the options framework, each option is defined by a tuple of policies, initiation states, and termination states. The set of termination states of an option is determined by a termination function which maps the state space to its class membership probability of the termination state set. Various advancements in the options framework, like the option critic architecture (Bacon et al., 2017), have significantly improved the convergence of the overall algorithm but most recent works focus on a fixed set of options that are hard to scale in practical scenarios.

Research has shown that the primary reason why humans excel at learning new skills from previously unseen and unknown environments is that we possess an inordinate amount of prior information. This can be in the form of implicit understanding of relations between different objects, knowledge of the physics governing the environment, and more importantly a well-defined set of skills (Dubey et al., 2018). For an RL agent to learn efficiently in complex environments, it too needs to rely on its previously learned knowledge so that it can continually improve its overall policy. In this spirit, in this paper, we propose an algorithm in which policies are learned sequentially, so that during the training of any policy, the knowledge obtained till then, in the form of the already trained previous policies, can be leveraged to inform the learning of the current policy.

Our algorithm is designed to operate in a framework wherein a major component of the goal of the RL agent is to learn such diverse skills as to prolong the episode and survive or stay alive. We call our method Stay Alive with Many Options. This behavior is incentivized by emitting a reward signal of −1 when the episode ends and a reward signal 0 for every other time step.

Conceptually one may draw parallels between our approach and curriculum learning (Bengio et al., 2009). The idea behind curriculum learning is to train a model with a curriculum that is a sequence of tasks of increasing complexity rather than simply allowing the model to learn the original task from scratch. In practice, it has been demonstrated that this approach significantly outperforms traditional learning methods (Elman, 1993). However, the major disadvantage of curriculum-based RL is that it is generally expensive to create a comprehensive curriculum, if not outright impracti-
cal. In our approach, when a new option is added, its policy is trained only in states in which the previously trained options are expected to perform poorly. This is done by using the termination functions of the options to effectively partition the state space so that each option can learn an optimal policy for some subset of the state space, which is an easier task to accomplish. The options are then chained together with the termination state of the previous option serving as the initial state of the next.

We evaluate our proposed method on two environments: (i) a flexible 3D navigation environment developed by us, and (ii) the Atari River Raid environment. By conducting extensive experiments, we establish that our method outperforms the state-of-the-art soft actor-critic algorithm (Haarnoja et al., 2018) and its options counterpart (Lobo & Jordan, 2019), the soft-option critic. Our main contributions are as follows.

(1) We propose a new approach called ‘Stay Alive with Many Options’ for training options, where the primary objective of the agent is to prolong the length of the episode. We show that various scenarios of practical interest involve such an objective.

(2) We demonstrate the utility of sequentially adding new skills without a policy over options with experimental results that outperform prior methods in the task of navigation in a simulated 3D environment and the Atari River Raid environment.

(3) We show that our approach can learn skills to solve complex tasks involving high-level goals in the navigation environment outperforming the state-of-the-art.

2. Related Work

The concept of temporal abstraction in reinforcement learning has been extensively explored in various works, from humble beginnings with options framework (Sutton et al., 1999), feudal learning (Dayan & Hinton, 1993), hierarchical abstract machines (Parr & Russell, 1998) and the MAXQ hierarchical learning algorithm (Dietterich, 2000) to recent endeavors in imagination augmented agent learning with variational temporal abstraction (Kim et al., 2019). Approaches like feudal networks (Vezhnevets et al., 2017) based on feudal learning fused a manager network to choose the direction of navigation in the latent space when learning workers (sub-policies).

The option-critic architecture (Bacon et al., 2017) builds on top of the options framework and makes use of the policy over options to learn its corresponding Q function. This acts as a critic and is used to update the termination functions of the options. Recently Soft Option Actor-Critic Architecture (SOAC) extended this approach by appending intrinsic rewards into the framework (Li et al., 2020). Unlike (Bacon et al., 2017) which used option critic to compute gradients for each sub-policy, we are concerned with learning sub-policies one at a time.

Hierarchical reinforcement learning with off-policy (Nachum et al., 2018) provided a data-efficient method of training hierarchical policies. Hindsight experience replay (Andrychowicz et al., 2017) has widely been adopted for training policies in sparse reward environments and has also been recently used in multi-level hierarchical reinforcement learning algorithms (Levy et al., 2019). Hierarchical reinforcement learning has also shown remarkable success in very complex domains like playing the game of Starcraft (Vinyals et al., 2017), although the sub-policies were trained separately and combined together by a master policy the agent learned to play the game like a pro player (Pang et al., 2019).

Meta-learning approaches like that by Frans et al. (2018) focused on training a meta controller that would be frequently re-initialized such that it can learn to control the trained sub-policies. Our approach amounts to partitioning the state space based upon how well a policy performs in it, much like previous iterative approaches (Mankowitz et al., 2016). Our method also shares some commonality with the deep skill chaining algorithm (Bagaria & Konidaris, 2019) on how new options are added to the existing set of options. Deep skill chaining sequentially learns local skills by chaining them backward from a goal state. However, in our approach, skills are learned to complement the previously acquired ones such that the agent can traverse to various unseen states. This method shares a striking resemblance with curriculum based learning approaches (Bengio et al., 2009) but here the curriculum naturally arises from the necessity of traversing the environment. The use of nested beta termination functions in our framework is inspired from the continual learning architecture in progressive neural networks (Rusu et al., 2016). We make use of the Soft-Actor Critic algorithm (SAC) (Haarnoja et al., 2018) that is based on maximum entropy reinforcement learning framework (Ziebart, 2010) for the training of all our policy networks.

3. Background

A Markov decision process (MDP) is defined by the tuple \((S, A, p, r, \gamma)\), where \(S\) is the state space, \(A\) is the action space, \(p\) is the state transition probability \(p(s_{t+1}|s_t, a_t)\) of the next state \(s_{t+1} \in S\) from state \(s_t \in S\) given an action \(a_t \in A\), \(r\) is the reward function \(r(s_t, a_t) \in \mathbb{R}\) that provides a reward signal as the agent traverses the environment, and \(\gamma \in [0, 1]\) is the discount factor. The aim is to find an
optimal policy $\pi^*$ such that

$$\pi^* = \arg \max_{\pi} \sum_{t=0}^{T} E_{(s_t, a_t) \sim \rho_\pi} [\gamma^t r(s_t, a_t)],$$

where $\rho_\pi$ is the state-action distribution induced by a policy $\pi$. For every policy $\pi$, one can define its corresponding $Q$ value function:

$$Q_\pi(s_t, a_t) = r(s_t, a_t) + \gamma E_{s_{t+1} \sim \rho(\cdot|s_t, a_t)} V_\pi(s_{t+1}),$$

where $V_\pi(s_t)$ is the value function defined by

$$V_\pi(s_t) = E_{a_t \sim \pi} [Q_\pi(s_t, a_t)].$$

### 3.1. Soft Actor-Critic

The soft actor-critic algorithm introduced by Haarnoja et al. (2018) is an off-policy entropy-based reinforcement learning algorithm. The main idea in the entropy-based learning approach is maximizing the entropy of our policy along with the task of reward maximization. A straightforward way of doing this is by making the reward function depend on the entropy of the current policy. Making the reward proportional to the entropy incentives greater exploration of the environment ensuring the policy is far less likely to get stuck in a local optimum, where one finds the optimal policy

$$\pi^* = \arg \max_{\pi} \sum_{t=0}^{T} E_{(s_t, a_t) \sim \rho_\pi} [\gamma^t r(s_t, a_t) + \alpha \mathcal{H}(\cdot|s_t)],$$

where $\alpha$ is the temperature variable which accounts for the importance of the entropy and $\mathcal{H}(\cdot|s_t)$ is the entropy of the policy. The above formulation reduces to the standard reinforcement learning objective as $\alpha \rightarrow 0$. It is shown by iteratively using the soft policy evaluation and soft policy improvement the policy convergences to the optimal policy $\pi^*$ (Haarnoja et al., 2018).

The temperature variable $\alpha$ can itself be treated as a parameter in the training process for better performance of the algorithm (Haarnoja et al., 2018). Making $\alpha$ a trainable parameter gives the algorithm the flexibility to dictate the relative importance of the policy’s entropy. As $\alpha$ decreases, the algorithm becomes more deterministic in nature and we make use of this property of the soft actor-critic to decide when new policies should be added.

### 3.2. The Options Framework

The idea of temporally extended actions has been introduced by (Sutton et al., 1999). An option is defined by the tuple $(\mathcal{I}_o, \pi_o, \beta_o)$, where $\omega \in \Omega$, the set of options, $\pi_o$ is the policy corresponding to the option, $\mathcal{I}_o(\subseteq S)$ is the set of states where the option can be initialized and $\beta_o : S \rightarrow [0, 1]$ is the termination function of the option. In a typical options framework $k$ sub-policies: $\{\pi_{\omega_1}, \pi_{\omega_2}, \ldots, \pi_{\omega_k}\}$ are initialized each with its corresponding $\mathcal{I}_o$ and $\beta_o$ along with a policy over options $\pi_\Omega$. In the call-and-return approach $\pi_\Omega$ chooses an option $\omega$ and $\pi_\omega$ executes actions till it terminates with probability $\beta_\omega(s_t)$ for a given state $s_t$ and the control then returns back to $\pi_\Omega$. The state transition dynamics are given by

$$P(s_{t+1}, \omega_{t+1}|s_t, \omega_t) = \sum_\omega \pi_\omega(a|s_t)P(s_{t+1}|s_t, a_t) \cdot ((1 - \beta_\omega(s_t))1_{\omega_t=\omega_{t+1}} + \beta_\omega(s_{t+1})\pi_\Omega(\omega_{t+1}|s_{t+1})).$$

Unlike other approaches where the next option is chosen by a master policy $\pi_\Omega$, in our proposed approach, the next option to be executed depends on the termination state space of the previous options.

### 4. The Proposed Stay Alive Framework

#### 4.1. Class of environments

In this framework, the agent is tasked with prolonging the duration of the episode, which is incentivized by using a simple reward function $r(s_t, a_t, s_{t+1})$, whose value is $-1$ if $s_{t+1}$ is the final state of the episode, ad $0$ otherwise. Many real-life problems can be effectively cast as reinforcement learning problems with such a reward function and minimal information from the environment. Examples of such applications include autonomous vehicle navigation while avoiding collision (Kahn et al., 2018), (Shalev-Shwartz et al., 2016) and drone navigation (Kang et al., 2019). Tasks that require the agent to maintain an equilibrium in an ever-changing environment may be cast into our framework using this simple reward function.

Practical examples may involve tasks like assembly line automation with increasing levels of complexity. A very interesting effect of using such a reward signal is that as the agent fails less frequently in the process of learning better policies, it becomes harder to train it owing to the increasing sparsity of the failure states. Our approach is designed to overcome this by learning new policies near states where failure occurs without disturbing the already learned policies.

In our proposed approach, the policies learned are need to be only locally optimal. The main challenge of the learning algorithm then becomes determining how likely the current policy will fail, so as to switch to another policy. Unlike other option learning algorithms, the proposed stay alive strategy is to train only one option at a time since it requires fewer data and is easier to train. In order to learn from a minimal amount of data for training, the stay alive approach does not train a (master) policy over the options but relies on the termination functions of individual options to determine
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Figure 1. The state spaces where the nested beta function classifies the current state as a non-termination state (represented as ovals).

which option should be chosen for execution. The policies are learned sequentially and the states in which a new policy is trained are determined by the termination functions, which are treated as binary classifiers. New policies are learned only in states that are classified as termination states for all the previous options and this is achieved by nesting the termination functions of the options. We explain this procedure in detail in the later subsections.

Ideally, one can continue to add more options into the set of all options until $V_t(s_t) \approx 0$, where state $s_t$ belongs to the marginal state distribution induced by the set of policies $\Omega$ learned by the algorithm. However, from a pragmatic perspective, we threshold the maximum number of options to be learned. We now describe in detail how each component of the framework is adopted in our approach.

4.2. Training Policies

In the proposed approach the first policy is trained as in traditional RL till a semi-optimal policy is obtained. In the next section, we formally define when we consider a policy to be semi-optimal. Depending on how the policy performs, the state space is portioned into termination and non-termination states as mentioned earlier. While training the next policy, learning takes place in the states that are classified as termination states by $\beta_{\omega_1}(s_t)$ so that the new policy is only focused on traversing states where previous policy failed. In order to make use of the previously learned policy, we also incentivize the new policy to traverse to states that are deemed non-termination states by $\beta_{\omega_1}(s_t)$ so that the new policy is low enough to warrant it to be considered a semi-optimal policy when $\alpha_{min} \in [0, 1]$ is a threshold. All new sub-policies are initialized with $\alpha = 1$ to ensure maximum exploration near states where policies are initialized. Essentially we augment a new policy when the temperature variable $\alpha$ of the currently trained policy is low enough to warrant it to be considered an optimal policy near its initialization states.

As the value of $\alpha$ decreases, there is a lesser incentive for the agent to maximize the entropy. This results in the learned policy becoming less exploratory and more deterministic. We determine a policy to be sufficiently trained for it to function as a semi optimal policy when $\alpha < \alpha_{min}$, where $\alpha_{min} \in [0, 1]$ is a threshold. All new sub-policies are initialized with $\alpha = 1$ to ensure maximum exploration near states where policies are initialized. Essentially we augment a new policy when the temperature variable $\alpha$ of the currently trained policy is low enough to warrant it to be considered an optimal policy near its initialization states.

Once a policy $\pi_\omega$ is trained enough to be deemed semi optimal, we fix that policy and no longer train it. The rationale for this is that it is much easier to train new options in the context of fixed already trained options, rather than trying to learn new options while simultaneously updating old options.

This results in the policy being skewed, severely, to increase the likelihood of the policy to generate actions that can quickly transition to states that are classified as non-termination states of the previous set of options. We show in later ablation studies that this is the primarily reason behind our approach outperforming the soft actor critic algorithm in the navigation environment.

The policy is updated as in soft-actor critic, by using the information projection on the exponential of the soft Q-value:

$$
\pi^\text{new}_\omega = \arg \min_{\pi'} D_{KL} \left( \pi'(.|s_t) \bigg\| \frac{\exp\left(\frac{1}{\alpha} Q^\pi_{\omega}(s_t, .)\right)}{Z^\pi_{\omega}(s_t)} \right),
$$

where $Z^\pi_{\omega}(s_t)$ normalizes the distribution.

In this work, we make use of the trainable $\alpha$ of the soft actor-critic algorithm as a measure to decide whether to stop training a policy and add a new option. The objective for computing the gradients of $\alpha$ is (Haarnoja et al., 2018):

$$
J(\alpha) = E_{a_t \sim \pi_1} \left[ -\alpha \log \pi_t(a_t|s_t) - \alpha \bar{H} \right],
$$

where $\bar{H}$ is a hyperparameter set to $-\dim(A)$, where $A$ is the action space. When $\alpha \in [0, 1]$ the optimal value of $\alpha$ which satisfies the above objective is 0 (as $-\log \pi_t(a_t|s_t) - \bar{H} \geq 0$) and the value of $\alpha$ monotonically decreases as the training progresses.

switch to some other policy which has already been fully trained and hence is presumably more capable of traversing those states. This encourages the agent to leverage previously gained knowledge instead of trying to relearn it. The training of the new policy is limited to those state-action pairs which are vital for prolonging the episode and cannot be delegated to previous policies.
4.3. Learning Termination Functions

Suppose the learning algorithm has already trained $k - 1$ options and the aim is to learn a new option $\omega_{new}$. $\tilde{\beta}_\omega(s_t)$ is either 0 or 1, which is obtained by using $\beta_\omega(s_t)$ as a binary classifier. In such a scenario one can train the new policy as if a single policy is being trained in all states $s_t$ satisfying $\tilde{\beta}_\omega(s_t) = 1$ for all $\omega \in \Omega_{old}$, where $\Omega_{old} = \omega_1, \omega_2, ... \omega_{k-1}$ and $\omega_{new} \notin \Omega_{old}$ (i.e., in states which are classified as the termination state by all the previous policies).

Given that we choose to adopt $\tilde{\beta}_\omega(s_t)$ as a discrete function, it is imperative that $\beta_\omega(s_t)$ is updated correctly else it could compromise the training of new policies altogether. Traditionally, in the options framework, each option has its own termination function. We differ from this approach by training nested $\beta_\omega$ functions. Rather than training $\beta_\omega_i$ for the $i^{th}$ policy we train $\beta_{\omega_1, \omega_2, ..., \omega_i}$ which is conceptually the termination classifier for the set of options $\omega_1, \omega_2, ..., \omega_i$ and its corresponding $\beta_{\omega_1, \omega_2, ..., \omega_i}$. As we incorporate new options the non-termination states of $\beta_{\omega_1, \omega_2, ..., \omega_i}$ should at least contain all the non-termination states of $\beta_{\omega_1, \omega_2, ..., \omega_{i-1}}$ because the new set of policies should be at least as good as the previous set of policies. As the new policies are trained in the termination states of the previous set of options the set of non-termination states for new policies can be expected to increase as shown in Figure 1. Without nested functions, as the number of options increases, it becomes more difficult to accurately update the individual beta functions of each policy, which in turn makes it difficult to incorporate new skills. In the proposed approach, as long as the last nested beta function is correctly updated, new policies can always be learned in the termination states of that function.

To obtain $\tilde{\beta}_{\omega_1, ... \omega_i}(s_t)$, one simply needs $\tilde{\beta}_{\omega_1, ..., \omega_i}(s_t)$ and $\tilde{\beta}_{\omega_1, ..., \omega_{i-1}}(s_t)$ which is given by:

$$\tilde{\beta}_{\omega_i}(s_t) = (1 - \tilde{\beta}_{\omega_1, ..., \omega_{i-1}}(s_t)) \land \tilde{\beta}_{\omega_1, ..., \omega_i}(s_t)$$ (9)

The above equation imposes a simple constraint on choosing options for execution by not allowing a new policy to execute actions in states which are classified as a non-terminating state by the previous nested beta function. This is because we do not want new policies to be learned in the state space where old policies have already learned a viable policy. This leads to the partition of the state space by separate policies.

$\beta_{\omega_1}$ is trained like a standard Q-value function using the negative reward signal emitted by the environment,

$$r_\beta(s_t, a_t, s_{t+1}) = \begin{cases} 1 & \text{if } s_{t+1} \text{ is the last state in the episode,} \\ 0 & \text{otherwise} \end{cases}$$ (10)

We overload the notation of $\beta_{\omega_1}$ by using as $\beta_{\omega_1}(s_t, a_t)$ as the termination function rather than $\beta_{\omega_1}(s_t)$ since we train it like a Q-value function and because it is a better estimator. As in the case of DQN it is TD updated using bootstrap:

$$\beta_{\omega_1}(s_t, a_t) \leftarrow r_\beta(s_t, a_t, s_{t+1}) + \gamma_\beta \beta_{\omega_1}(s_{t+1}, a_{t+1})$$ (11)

where $\gamma_\beta \in [0, 1]$ is the termination discount factor. It largely depends on the problem domain and directly impacts the newer policies that are trained by indirectly influencing the partition of the termination and non-termination states.

As new policies are incorporated, $r_\beta(s_t, a_t)$ becomes an increasingly sparse reward since the agent learns strategies to avoid failure and episodes become relatively longer. In such instances simply training $\beta_{\omega_1}(s_t)$ using only a TD update can bias it to predict all states as nontermination states thus, effectively preventing new policies from learning. To avoid this, after the new policy has been semi-optimally trained, the termination function is trained using the binary cross entropy loss as follows:

$$\beta_{\omega_1}(s_t, a_t) \leftarrow \arg \min_{\beta_{\omega_1}} - \mathbb{E} \left[ y_t \log \beta_{\omega_1}(s_t, a_t) + (1 - y_t) \log(1 - \beta_{\omega_1}(s_t, a_t)) \right].$$ (12)

Here the labels $y_t$ is the solution to (11) if the policy that generates the actions is fixed. It is obtained by unrolling a trajectory $\{s_0, ..., s_{T-1}\}$ and labeling it as $y_t = \gamma_\beta T^{-1 - t}$, where $\gamma_\beta$ is the discount factor.

As we fix the policies after training them, the cross entropy update gives us a better estimation as compared to the previous TD updates. To make $\beta_{\omega_1}(s_t, a_t)$ unbiased, an equal number of probable termination and nontermination states are sampled for training. The major advantage of adopting nested termination functions is that we only need to modify the latest termination function to correctly reflect if a state is a termination state or not. That will then be used to determine the states in which the next new policy will be trained. Given a training set $\Omega$ of options, an option is chosen during execution according to the constraint given in Equation (9). Algorithm 2 explains this in further detail.

5. Experimental Results

We compare our approach on several navigation environments against the Soft Actor critic (SAC) (Haarnoja et al., 2018) and the Soft Option-Critic (SOC) (Lobo & Jordan, 2019) algorithms. A detailed description of the environment, the network architectures, and the hyperparameters used can be found in the Appendix. A video demonstration is also provided in the supplementary materials.
5.1. The 3D navigation environment

The 3D simulated environment is created with the Panda3D game engine (Goslin & Mine, 2004) for collision avoidance where the agent is a vehicle that moves with a constant velocity. This collision avoidance environment consists of long corridors twisting and turning as the agent navigates inside of it. The primary challenge in the environment is that agent has to understand whether left or right turn is coming up as taking a wrong turn will inevitably end the episode. The results of our 3D navigation environment given in Figure 3(a). We also validated our approach on a sparse goal-based version of the environment and the results can be found in the supplementary material.

5.2. 3D Color Navigation environment

The colored version of the environment takes RGB images as input as opposed to grayscale images as shown in Figure 3b. Here the agent is tasked with taking the correct direction depending on the color of the walls it sees in front of it. It should understand the high-level concept of taking a turn in the direction of the colored wall if the color is green or in the opposite direction if the color is green. Taking the wrong turn leads to termination of the episode in the next few time steps. Figure 3(b) shows the results for the color environment.

5.3. River Raid environment

The Atari River Raid is a top-down shooting game where the goal is to maneuver a plane to destroy or avoid obstacles like tankers, helicopters, jets, and bridges to continuously keep moving forward all the while not crashing into the walls on the sides or the obstacles themselves. Destroying the obstacles rewards the player with an increase in overall points obtained in the game, the plane also needs to refill its fuel which it loses continually as the game progresses and which is refilled by hovering over fuel tanks (which can also be destroyed for obtaining points) which frequently spawn in the environment. The plane crashes when it either collides with an obstacle or runs out of fuel.

For our experiments, we modify the reward function of the environment to emit $-1$ reward when the agent crashes and a 0 reward for every other time step. We also restrict the agent to use a reduced number of actions while navigating in the environment such that is not allowed to slow down the plane, our modified action set has 6 discrete actions the agent can take as compared to 18 in the original gym implementation. We follow the same preprocessing of the input image and network architecture as used by Mnih et al. (2013). Since the reward is extremely sparse in such a setting, we store only the last 25 time steps in the replay buffer for better training. The results are shown in Figure 3(c).

5.4. What the policies learn

A crucial aspect of our approach is the generalization of the nested termination functions which is used to provide intrinsic rewards to the new policies. As mentioned previously we do not train the previous nested termination functions so the generalization of these functions to unknown state spaces has a significant impact on the overall training of policies. In Figure 4 we show a snapshot of the learnt policies navigating in the environment. The first option simply learns to move straight in the environment while the second and third policies learn to take the correct turns.

6. Conclusion

In this paper, we have proposed a framework called stay alive framework, which allows adding new skills dynamically in the absence of a policy over options. We provide a simple method by which diverse skills can be incorporated in an overall skill set in environments where the objective is to prolong the episode and shown that these outperform prior methods.

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Figure 3. The results obtained on the environments

(a) 3D environment with 3 options  (b) Color 3D environment with 3 options  (c) Atari environment with 2 options

Figure 4. Learnt policies obtained after training 3 options. $\pi_{\omega_1}$: orange, $\pi_{\omega_2}$: blue, $\pi_{\omega_3}$: green. Each policy outputs a Gaussian distribution, the active policy is the one in filled with color.

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A. The developed 3D environment

As mentioned in the paper, we have created a custom simulated 3D navigation environment using the Panda3D game engine (Goslin & Mine, 2004). Here we present the details of this environment.

The agent receives the past K gray-scale images re-scaled to $36 \times 64$ pixels as input and outputs an action $a_t \in \mathbb{R}$, every time a collision occurs and the episode is reset. The agent takes an action every 0.25 seconds in the environment and receives a continuous stream of 0 rewards in each time-step except when it collides with the walls where the episode ends with a $-1$ reward. Overall, the environment is a rather simplistic one with mono-colored white walls, minimalist texture, and ambient lighting. An interesting aspect of this environment is that the single source lighting creates different shades on the walls depending on the direction they are facing, so the agent has to learn to turn depending on its understanding of what turn is coming up while disregarding the shade of the wall.

In the colored navigation environment (Figure 6) the agent has to follow a path specified by the color of the walls in front of it to take the correct direction. Two contiguous block segments are coloured to indicate the direction that the vehicle is supposed to take and the color determines if the direction is correct or not. Green indicates that the turn is the correct one while red is incorrect and the vehicle should take the turn in the opposite direction as shown below.

Videos of the trained options for both environments are

\begin{algorithm}
\caption{Training an option}
\begin{algorithmic}
\State $\Omega = \{\omega_1, \omega_2, \ldots, \omega_{k-1}\}$ a set of $k - 1$ options and $\alpha_{\text{min}}$ the threshold 
\State Initialize environment $E$
\State Initialize replay buffer $\mathcal{R}$
\State Initialize new option $\omega_k = \{\pi_{\omega_k}, \beta_{\omega_1}, \ldots, \beta_{\omega_k}\}$
\State $\alpha_{\omega_k} \leftarrow 1$
\While{$\alpha_{\omega_k} \geq \alpha_{\text{min}}$} 
\State $\beta_{\omega_k} \leftarrow 1$
\If{$\Omega \neq \emptyset$} 
\State Get $a_t$ from $\Omega$ for state $s_t$ and update $i$ as shown in algorithm (2)
\State $\beta_{i} \leftarrow$ classify using $\beta_{\omega_1}, \ldots, \omega_{k-1}(s_t, a_t)$
\EndIf
\If{$\beta_{i} = 1$} 
\State $i \leftarrow 1$
\State $a_t \sim \pi_{\omega_k}(s_t)$
\EndIf
\State Execute action $a_t$ in the environment $E$ to get the next state $s_{t+1}$ and the reward $r_t$
\State $r_{\beta_{i}} \leftarrow -r_t$
\If{$\Omega \neq \emptyset$ and $\beta_{i} = 1$} 
\State Get $a_{t+1}$ from $\Omega$ for state $s_{t+1}$ as shown in algorithm (2)
\State $\beta_{i+1} \leftarrow$ classify using $\beta_{\omega_1}, \ldots, \omega_{k-1}(s_{t+1}, a_{t+1})$
\If{$\beta_{i+1} = 0$} 
\State $r_{i} \leftarrow 1$
\EndIf
\EndIf
\If{$\beta_{i} = 0$} 
\State Store transition tuple $(s_t, a_t, s_{t+1}, r_t, r_{\beta_{i}})$ in replay buffer $\mathcal{R}$
\State Update $\pi_{\omega_k}$ and $\alpha_{\omega_k}$ with $(s_t, a_t, s_{t+1}, r_t)$ sampled from $\mathcal{R}$ with the soft actor critic update
\State Update $\beta_{\omega_1}, \ldots, \omega_{k-1}$ with $(s_t, a_t, s_{t+1}, r_{\beta_{i}})$ sampled from $\mathcal{R}$ with TD update
\EndIf
\EndWhile
\State Add $\omega_k$ to the set of options $\Omega$
\State Initialize buffer $\mathcal{D}$
\State Roll-out trajectories in the environment as described in Algorithm (2) and store them in $\mathcal{D}$
\State Train $\beta_{\omega_1}, \ldots, \omega_{k}$ with $(s_t, a_t, y_t)$ sampled from $\mathcal{D}$ using the binary cross entropy loss as shown in equation (12)
\end{algorithmic}
\end{algorithm}
provided in the supplementary materials. In each time step, the mean of the normal distribution is always selected for the purposes of evaluation and the selected option is highlighted with filled color. Each Gaussian distribution corresponds to the output of a specific policy.

### B. Training goal-based agents

The class of environments that we described in this work captures many practical scenarios. For example, many goal-based navigation environments can be modeled using this approach. Here, we consider one such goal-based environment (Figure 7), where the objective of the agent is to navigate corridors according to a specified instruction. The instruction is given as a one-hot vector input that corresponds to the corridor the agent is supposed to navigate to (left, center or right for instructions $[1, 0, 0]$, $[0, 1, 0]$ or $[0, 0, 1]$ respectively). For this, a reward function can be defined as,

$$\begin{align*}
r(s_t, a_t, s_{t+1}) = \begin{cases} 
0 & \text{if } s_{t+1} \text{ is not last state} \\
1 & \text{if } s_{t+1} \in S_{\text{goal}} \\
-1 & \text{if } s_{t+1} \in S_{\text{collision}} \\
-\frac{1}{2} & \text{otherwise.}
\end{cases}
\end{align*}$$

Here, $S_{\text{goal}}$ denotes the state space, where the agent reaches the goal by navigating to the correct corridor according to the given instruction, and $S_{\text{collision}}$ represents the set of all states where the agent collides with the walls in the environment. The agent incurs a $-0.5$ reward when it enters the wrong corridor. This is given in order to deter the agent from choosing the wrong corridor, although not as great of a deterrent as colliding with the walls. However, using this reward function may also produce policies that easily fall into a local optimum of choosing a single direction by completely disregarding the instruction.

One can easily modify the proposed approach for training on this environment by including the state where the agent has taken a wrong direction in the termination state set, and the state where it has taken the correct direction in the non-termination state set for the purposes of training the termination function. The options are also made to execute for some minimum time steps $t_{\text{min}}$ before switching to another option. This is done to prevent options from switching prematurely (Harb et al., 2018). We report the results of our approach with 2 options (Figure 8) and compared it against Hindsight Experience Replay (Andrychowicz et al., 2017) using Soft Actor Critic with priority buffers (Schaul et al., 2015). We use the same hyper-parameters as in 3D
navigation environment in the previous with the exception of \( K = 20 \) and \( \gamma \beta = 0.95 \) along with \( t_{\text{min}} = 16 \).

C. Details on the Network Architecture

The agent receives a \( 64 \times 36 \) image from the 3D navigation environment every time step. The image encoder shown in Figure 9(a) converts the last \( K \) images the agent receives from the environment into the corresponding state vector. Each image is passed through a series of 2D Convolution networks with ReLU activation, then the output is flattened to a vector and stacked with all the \( K \) time step outputs \([s_0, s_1, ..., s_{K-1}]\). The 2D convolution networks use shared weights and were implemented using a single network parallelly processing the \( n \) channel images. In the scenario of simple navigation, the input is grayscale with \( n = 1 \), and for the color environment, it is an RGB image with \( n = 3 \). The input to the series of 1D convolution network is \((K, 64)\) and the resulting output is a 256 dimensional vector, which is the current state vector which is the input to the policy and Q networks.

The policy returns \((\mu, \sigma)\) and action \( a_t \) is obtained by taking the hyperbolic tangent: \( \tanh(x) \), where \( x \sim \mathcal{N}(\mu, \sigma^2) \) as shown in Figure 9(b). The action in the 3D navigation environments is a 1 dimensional continuous action \([-1, 1]\) corresponding to the angle of the steering wheel of the simulated vehicle for the specific time step \( t \), for each time step is simply \( 30 \times a_t \). The Q network architecture as shown in Figure 9(c) is almost identical to the policy network, except it also concatenates \( a_t \) along with the state vector obtained from the image encoder, the action passed through some linear layers with ReLU activation before concatenation. The termination function \( \beta \) has the same architecture like that of the Q value networks followed by a sigmoid function.

For the Riverraid environment, we use the exact same architecture as in the DQN (Mnih et al., 2013) with identical policy and Q networks. Since this a discrete action space, for the purposes of training the network, we make use of the soft actor critic for discrete action setting (Christodoulou, 2019).

For the implementation of the soft option critic, we made use of shared networks with an additional parameter \( o_t \), which is the one-hot vector representation of the option selected at the time. As with action \( a_t \), the one-hot vector \( o_t \) is also passed through a similar network before being concatenated with the state vector.

D. Inter Option Rewards

As mentioned in the paper we make use of internal rewards when training subsequent policies in a serial manner. Each policy is incentivized to traverse to a state space where the previous set of policies determines it is capable of traversing it, using the reward function:

\[
    r_{\pi_{\omega_i}}(s_t, a_t, s_{t+1}) = \begin{cases} 
    r(s_t, a_t, s_{t+1}) & \text{if } \tilde{\beta}_{\omega_{i-1}}(s_{t+1}, \cdot) = 0 \\
    1 & \text{otherwise}
    \end{cases}
\]

Figure 10. Results obtained on the 3D navigation environment with 4 options.

This greatly improves the convergence of the algorithm in scenarios where the previous policies need to be used repeatedly and rather frequently. In our 3D navigation environment, in the absence of the \(+1\) reward, the new options require much more training for them to traverse to desired states by taking correct turns. We demonstrate this by training our method without providing the extra \(+1\) reward using 4 options. Figure 10 shows the results of our approach and Figure 11 shows the result of our approach in the absence of the \(+1\) reward.
Stay Alive with Many Options

(a) Image Encoder

(b) Policy Network

(c) Q network

Figure 9. Network architecture

of the internal reward.

Figure 11. Results obtained on the 3D navigation environment with 4 options without inter option rewards.

E. Details on Hyper-parameters

All our experiments make use the Adam optimizer (Kingma & Ba, 2015) and all buffers used to store roll-out trajectories after a policy has been trained for BCE updates have a maximum size of 1000. The hyperparameters used for experiments in the 3D navigation environment, the 3D color navigation environment and the Atari Riverraid environment are provided in Tables 1, 2 and 3 respectively.

| Parameter                          | Value       |
|-----------------------------------|-------------|
| learning rate                     | $3 \times 10^{-4}$ |
| discount factor($\gamma$)         | 0.99        |
| replay buffer size                | $10^4$      |
| target smoothing coefficient($\tau$) | 0.005    |
| number of frames in input state ($K$) | 10       |
| batch size                        | 16          |
| alpha threshold ($\alpha_{min}$)   | 0.1         |
| termination discount factor ($\gamma_{\beta}$) | 0.95    |

In the 3D navigation environment, only the first policy’s termination function is not updated using binary cross-entropy as mentioned in the paper, as it tends to generalize rather well.

Each experimental plot has been plotted by taking the mean
Table 2. 3D Color Navigation environment

| Parameter                  | Value          |
|----------------------------|----------------|
| learning rate              | $3 \times 10^{-4}$ |
| discount factor ($\gamma$) | 0.99           |
| replay buffer size         | $10^4$         |
| target smoothing coefficient ($\tau$) | 0.005        |
| number of frames in input state ($K$) | 10             |
| batch size                 | 16             |
| alpha threshold ($\alpha_{min}$) | 0.01         |
| termination discount factor ($\gamma_{\beta}$) | 0.9          |

Table 3. Atari Riverraid environment

| Parameter                  | Value          |
|----------------------------|----------------|
| learning rate              | $3 \times 10^{-4}$ |
| discount factor ($\gamma$) | 0.99           |
| replay buffer size         | $10^4$         |
| target smoothing coefficient ($\tau$) | 0.005        |
| number of frames in input state ($K$) | 4              |
| batch size                 | 16             |
| alpha threshold ($\alpha_{min}$) | 0.01         |
| termination discount factor ($\gamma_{\beta}$) | 0.95         |

of 5 different experiments and the corresponding bounds are given $\pm \text{std}/2$.

F. More Experiments

To demonstrate the effectiveness of our method irrespective of the number of options chosen, we trained our algorithm on the Atari River Raid environment making use of 3 options. We see that the performance of our algorithm is improved by the addition of an extra option, whereas the performance of SOC and SAC remain the same.

![Figure 12. Results obtained on the Atari River Raid environment with 3 options](image_url)