Learning Diverse Goal-Conditioned Policies for Frontier Selection in Navigation

Ganesh Iyer*
giyer@andrew.cmu.edu

Vidhi Jain*
vidhij@andrew.cmu.edu

Abstract: Learning end-to-end policy for navigation with a focus on intelligent exploration is a difficult task in robotics. While methods like soft-Q learning and ensembles of policies can demonstrate navigation behaviors in completely observed maps, we currently do not have ways of extending these policies to unexplored or partially explored environments. To this end, we propose a hierarchical formulation to tackle the problem of learning based efficient exploration. We decompose the the task into two sub-problems: selecting the next best goal in the visible space, followed by efficiently navigating to this space in the partial map setting. We propose a global policy network that learns the selection of the next best goal('frontier') in the observable space, followed by a local policy that learns low-level navigation conditioned on different goal embeddings in known environments. Our key approach to this decomposition is to enable the independent training of both of these components by creating randomized gridmaps on a large-scale for both subtasks. We demonstrate our approach by training both policies for navigation in the `FourRooms` environment in gym-minigrid. The final combined policy will, therefore, be an end-to-end differentiable policy for map exploration. Currently, we evaluate the performance of the goal-conditioned local policy. We present analysis of sparse reward based the global policy and compare the performance with a dense reward variant.

Keywords: Navigation, Exploration, Reinforcement Learning

1 Introduction

Navigation in known environments is considered to be solved efficiently by both planning and reinforcement learning (RL) based methods. This stems from the fact that if the complete information in map is available, optimal methods can be developed to solve point goal navigation tasks. While planning based approaches offer completeness and strong formal guarantees, the next feasible goals is often recorded and selected based on heuristics, like graph-based methods, or probabilistic sampling based methods for continuous spaces. However, tackling efficient navigation in unexplored maps is difficult cause it does not have a complete solution.

We propose a solution for the problem of unexplored-map navigation in gridmap environments, that is based on the selection of '**frontiers**'. Classically, we consider frontiers to be points at the boundary of known regions of a map, such that they can be considered important points to facilitate exploration in a map. Therefore, we define such frontiers as sub-goals, and learn a policy that can select such frontiers on partial grid maps.

When navigating in unknown environments, humans often invoke a decision criteria. This could be the next subgoal, and the decision could either be based on some semantic context, or some such prior. Learning how to select the next subgoal for higher level task such as coverage of the map is a challenging open question.

Assume that we have a policy that can choose the sutiable frontier to navigate, we also require another low level policy that can facilitate navigation to these sub-goals. This poses a challenge, since it can be difficult to develop differentiable planning frameworks. We, therefore, rely on a hierarchical approach and employ a second policy for action selection to navigate in known environments.

4th Conference on Robot Learning (CoRL 2020), Zurich, Switzerland.

Our key contribution is the decomposition of the map exploration process into a two stage approach that results in a hierarchical and modular differentiable policy for navigation in unknown environments – a "global" policy that can propose frontier locations that lead to high coverage, and a "local" policy trained on randomly generated submaps. This enables us to learn data-driven exploration strategies to later improve the global policy with different kinds of reward functions.

2 Related Work

Robot Navigation Our work heavily derives from frontier based robot exploration literature. The concept of frontiers for exploration of unknown spaces was first introduced in [1] by Yamauchi, in which regions on the boundary between known and unknown regions are considered valuable targets to explore to increase information about the environment. Traditionally, frontier based exploration is focused on geometric methods for navigation using SLAM, as demonstrated in works like [2], [3], and more recently deep learning based methods like [4].

More recently, active learning methods for navigation have been proposed as a solution to downstream robot control tasks, that propose to navigate end-to-end with implicit mapping. In many of these works, the selection of frontiers is implicit, and is attributed to semantic priors (Yang et al. [5]), or geometric priors (Chen et al. [6]). Some of the work that comes close to our work regarding the explicit use of frontiers is [7], where the expected cost value for each state action pair is calculated by observing trajectories of an optimistic planner.

Hierarchical Reinforcement Learning (HRL) We consider decomposing the actual reinforcement learning problem down into sub-problems such that solving them leads to a more efficient or powerful solution to the original problem. With the advent of Deep Learning, hierarchical representations are considered as an interaction between multiple policy networks. Such representations have been useful in solving all kinds of tasks. [8] was the first to introduce a hierarchical DQN (H-DQN) structures operating at different time scales to solve the sparse reward problem of Montezuma's revenge. [9] also propose a hierarchichal PPO formulation for the gym-minigrid [10] environments. More recently, hierarchical policies have also been used for embodied question answering. [11] decomposes the problem of navigation for question-answering into a planner and controller framework, with the controller pre-trained by imitation learning based method.

In contrast, our local policy, while similar in spirit to a controller focused on grid-like environments, is trained by reinforcement learning in randomized grid maps to enable generalization. Our work is very close to Chaplot et al. [12] which demonstrated such a hierarchical policy for pointgoal navigation tasks in 3D environments. Our method is different in two respects. Firstly, our local and global policies can be trained in a disjoint manner and combined to solve the task. Secondly, our global policy model can be decomposed to account for a soft representation, such that we can provide different exploration strategies for complete map exploration. Further, it is easy to see how our proposed global frontiers could also become pointgoals for navigation, although that is not the main focus of this work.

Learning based Planning We discuss this topic, since our local policy can be considered as a short term goal driven planner but trained as goal-conditioned RL, and our global policy utilizes an A* star planner for learning high-level policy. Eysenbach et al [13] propose search on the replay buffer that utilizes the value function of goal-conditioned reinforcement learning policy to add edge weights and create a graph structure of states represented as nodes. This serves the graph based planning techniques to plan waypoints to the goal.

Reinforcement Learning based approaches for planning have recently been proposed as differentiable planners for higher level tasks. These works leverage on unrolled dynamic computation graphs created in popular libraries to create differentiable planning mechanisms. Value Iteration Networks [14] by Tamar et. al couple attention mechanisms with value maps to account for differentiable planning in grid like discrete environments. Gated Graph Planning Networks [15] further improves on this by including long-term memory into their framework using LSTMs. In contrast to such explicit differentiable planning modules, our local policy is a goal driven policy network that is trained on randomized maps to improve efficiency. On grid-like environments, this has proven to be effective for local planning, as seen in works focusing on goal conditioned navigation, like [16].

3 Method

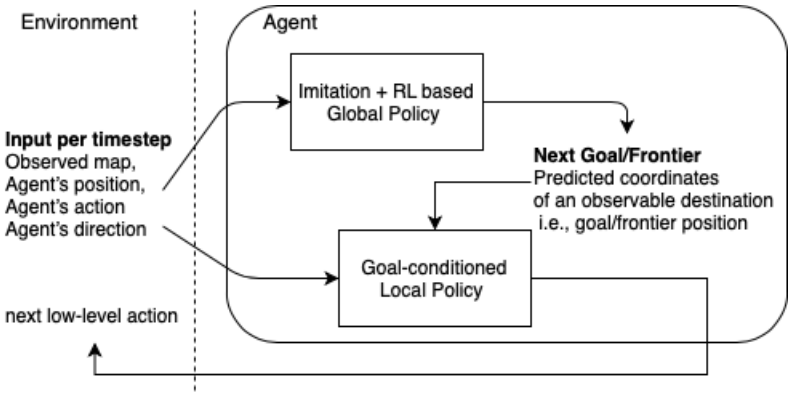


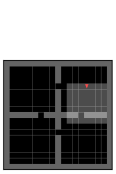
Figure 1: Proposed Architecture for integration of local and global policy

In partially observed environments, often, the reward signal is sparse since a reward is only achieved when an agent reaches a goal location. Further, this location in the map may not be currently observable, making this task difficult to train using off-the-shelf RL algorithms. However, abstracting the action space from low-level actions to frontier selection can help to alleviate this problem.

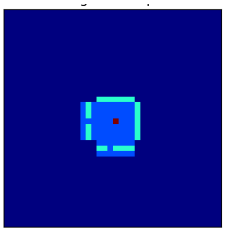
We propose to decompose the navigation problem into sub-components and learn them separately. First, we learn a local policy which can navigate to a given goal position in a known observed environment. Second, we learn a global policy to predict intended frontier/goal position in the observable space based on agent's map of the partially revealed environment, agent's position, direction, and previous history of actions. Figure 1 illustrates the integration architecture that shows how the global policy could provide the next frontier/goal coordinates to the local policy.

The local policy is a goal-conditioned reinforcement learning model which takes in the intermittent goal and executes next low level actions for navigation. Upon reaching the goal, this observation should trigger the global policy to predict another intermittent goal. The objective task is to maximize the coverage, as used in [12].

4 Experimental setup



(a) Environment



(b) Agent's observed map

Figure 2: The environment and agent's observed map at initialization. (a) the classic `Fourrooms` for **coverage** task, (b) the agent's observed view

We used the `FourRooms` environment in gym-minigrid [10], which is a 20x20 grid with a goal position, as shown in Figure 2a. Based on the partial observation of the agent, we construct the agent's observed map as shown in 2b to serve as the input to both global and local policy networks. Though our approach is tested with this setup, it can be generalized to other kinds of partially observable discrete environments. Note that our observation model in gridworld follows a partially observable markov decision process (POMDP), since we do not have access to the complete state information, mainly the map.

First, we extract the current observed map of the agent, agent's action and direction, along with the selected goal/frontier coordinates over multiple trajectories while exploring the map. These trajectories are collected using a graph-based planner, where sub-goals are provided as the nearest boundary value frontier from the current location of the robot. Note that this step could be replaced with actual human trajectories or human selected frontiers.

Given that the environment size is s, then agent view of the map is created such that the agent is always initialized at the center of a grid sized $2s$. However, the agent starts in the environment from a random location that not known a-priori. Thereon, the partial views from agent's observation are extracted and aggregated to represent the area observed so far by the agent. This map of observed area contains a compact encoding of whether the grid location is unseen, empty or is a wall for the `FourRooms` environment. In real world, this is analogous to discretizing the space into grid, using object detection module and maintaining a numeric encoding of different object types seen so far.

We train both the policies using the current observed map as seen by the agent. The agent is initialized with a random position and orientation in the grid map. It is important to note that we assume the agent has memory and as it traverses in the map, its belief over the map grows as visible regions. Further, this results in different partial grid-maps based on the initialization of the agent.

4.1 Local policy

The local policy is trained to navigate to a goal in fully observable environment such that the agent position, goal position and the observed partial map mask are all randomly selected for a given episode. These partial map masks are extracted from the trajectories obtained from the planner with the agent's construction of the observed map. Our custom environment in gym-minigrid enables the construction of fully visible environments with the partial map masks as shown in Figure 3. These masks are created based on a expert trajectories, which is a frontier based planner in our case.

In order to promote generalization to all kinds of partially observable submaps, we provide a curriculum-learning based strategy to introduce submaps during training, particularly, based on the the size of the submap. The intuition is that the bigger the submap, the complexity it is due to a larger possibility space of goal and agent starting points. Therefore, by providing a natural curriculum of increasingly diverse submaps, we hope alleviate the training complexity that comes with the training for long horizon navigation tasks. Due to navigation with complete observability in partial maps, we can modify the reward signal to incorporate a dense reward. We consider two types of possible reward functions:

Euclidean Distance:

$$R_t = \begin{cases} 100, & \text{if } p_{goal} = p_t \\ -\gamma(\sqrt{(p_{goal} - p_t)^2}), & \text{otherwise} \end{cases}$$

Shortest Path Length reward:

$$R_t = \begin{cases} 100, & \text{if } p_{goal} = p_t \\ -\gamma(C_{p_{goal} \sim G}[p_t]), & \text{otherwise} \end{cases}$$

Here, p_{goal} is the goal position, p_t is the position of the agent at time t, γ is a weight term, and $C_{p_{goal} \sim G}$ indicates the shortest distance in pixels from the goal p_{goal}. (For reference the heatmap in Figure 4(b) indicates the cost from the goal). For the experiments, we chose γ = 0.1.

To further understand the curriculum, Figure 3 shows some variations of the partially observable maps in FourRooms environment of gym-minigrid in order that they were provided at training time. Note that since we obtain these using a graph planner, each room may be variably explored based on the initial starting position, leading to a rich diversity in possible submaps.

To train the local policy, we use an asynchronous variant of the Proximal Policy Optimization (PPO) for learning this task. We use a convolutional LSTM network, that takes 40x40 input RGB gridmaps as input, and provides a discrete action selection as output. The convolutional netwoks consist of 4 convolutional layers with 64 filters and 2x2 kernel size. We use a LSTM hidden dimension size of 128. Both the actor and critic models have the same structure. We train for a total of 20000 submaps, with a repetition frequency of 20 episodes per submap and 8 parallel environments (3.2 million episodes). As an additional baseline, we also consider the task of exploration using only local views. An example of local views vs global views is best explained in the Figure 4. For this task, only a sparse reward is provided using the same curriculum strategy to promote exploration.

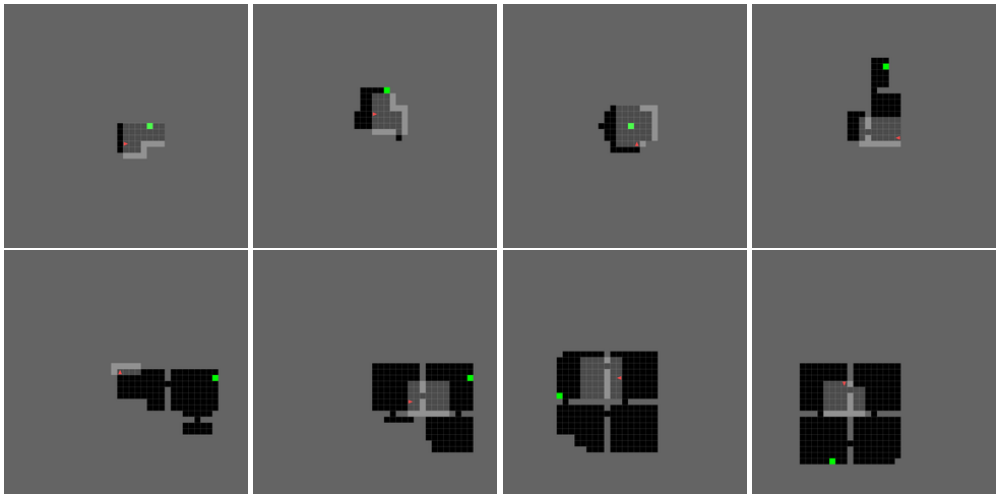


Figure 3: Left-Right: An example of the curriculum provided during training. We assume that the agent starts at the center (20x20) and proceeds to expand outwards based on its current direction and view point. Therefore, the agent builds a map as it completes the `FourRooms` environment. This curriculum simulates this experience explicitly in training.

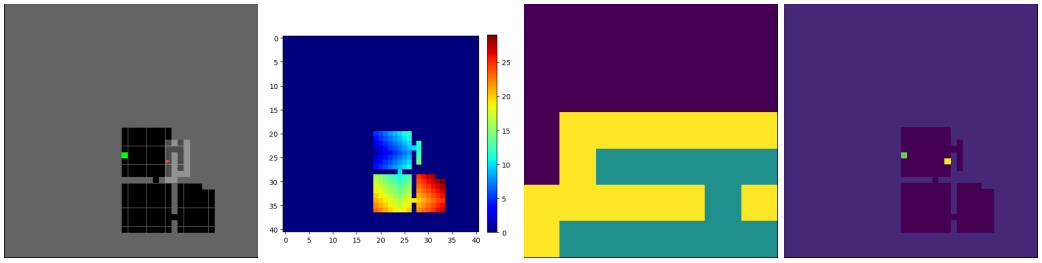


Figure 4: Left-Right (a-d): (a) shows the actual submap the agent is navigating in. (b) shows the cost to reach goal from all points in the submap. (c) indicates the local observation of the agent (baseline) (d) shows the global view as the observation

4.2 Global Policy

The global policy is trained to strategically cover all areas of the map when the agent can observe only limited field of view is available at a location per timestep. The global policy maintains the observed map so far from the agent's perspective.

Given the observed map view of the agent, the task of the global policy is to propose the coordinates where the agent should go next. The teleportation to the predicted coordinates are executed with A* planner. The coordinates are continuous valued inputs in $\{-1, 1\}$, and represented in terms of the distance r and the angle θ from the agent's frame of view. If the coordinates are outside the observed area so far, no path can be found by the planner and the agent does not move in this case.

To solve the coverage task in minimum number of steps, we train the global policy network with two variants in reward structures:

Sparse Reward The sparse reward is given only upon completion of the task of coverage of the map.

$$R^{sparse} = 1. - 0.9 \times (\text{step count / max steps})$$

where the max steps refers to the maximum number of coordinates that the global policy can propose.

Dense Reward The dense reward is provided at every coordinate proposed by the global policy. If the predicted coordinate is outside the observed area, the model is penalized by how far the coordinate is from the agent. If the predicted coordinate is within the observed area, the model is

rewarded based on the change in the observed area by moving to the new coordinate from previous one. Upon completion of coverage, the model is awarded a large bonus depending on the map and a similar penalty as in sparse reward setting. Overall, the dense reward is as follows:

$$R_t^{dense} = \begin{cases} -(\mathbf{g} - \mathbf{a})^2 & \text{if } M_t[\mathbf{g}] = 0 \\ M_{t+1} - M_t & \text{if } M_t[\mathbf{g}] = 1 \\ B - \text{step count} & \text{if coverage task is done} \end{cases}$$

where **a** represents the agent's position, **g** represents the proposed coordinates by the global policy, M_k represents the observed area mask at timestep k where unseen is 0, seen is 1, and B represents the large bonus on task completion, which is dependent on the map size.

5 Results

5.1 Local Policy

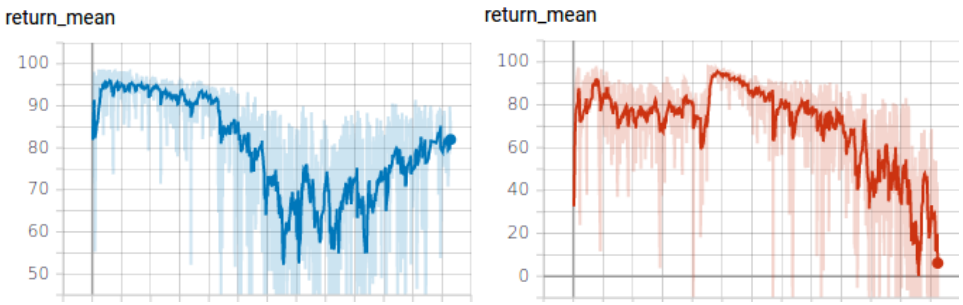


Figure 5: Mean Return of the local policy. Left: Trained using Euclidean distance reward, Right: Trained using Shortest Path Length reward

Figure 5 shows the mean return for the local policy. Note that this is with the curriculum training, so y-axis indicates the increasing map size. During training with euclidean distance, we notice a decrease in the mean return, but this improves over time, until the agent is comparably efficient at reaching the goal before the episode terminates. However, this is not the case for training with shortest path length reward. We hypothesize that since we were using the same submap update frequency it is possible that this is not enough for the shortest path reward and it may need additional epsiodes in the same submap before understanding this relationship.

5.2 Global Policy

In order to compare the performance of policies trained with different reward structure, we create an evaluation environment where both policies are evaluated in terms of the rewards obtained over

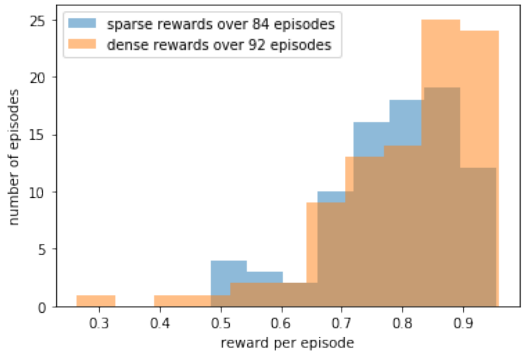


Figure 6: Comparison between sparse and dense reward training approach for global policy

20K total proposed coordinates. The reward structure for the evaluation environment is:

$$1. - 0.9 \times (\text{step count / max count}), \qquad \text{where max count} = 1000.$$

The results shown in the figure 6 are evaluated for sparse and dense variants of global policy where model was trained for 1 million total timesteps. Here timestep refers to the number of coordinates proposed by the policy. If the coverage task was done or maximum of 1000 coordinates were proposed, the environment was reset with different agent position and openings within the doors. We can see that the policy trained with dense reward successfully performs coverage on 92 episodes with mean reward of 0.81. On the other hand, sparse policy performs slightly worse by successfully completing only 85 episodes with mean reward of 0.78.

On training for both the global policy variants for 2 million timesteps, we observe that the sparse reward based policy improves as shown in figure 7 but the dense reward based policy collapses to a fixed value. This is evident in the drastic dip in the mean episode reward and a corresponding peak in the policy gradient loss in figure 8.

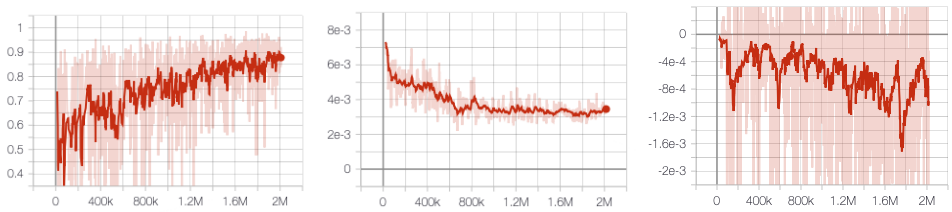


Figure 7: Training for sparse reward based global policy: (a) Episode reward. (b) value function loss. (c) policy gradient loss.

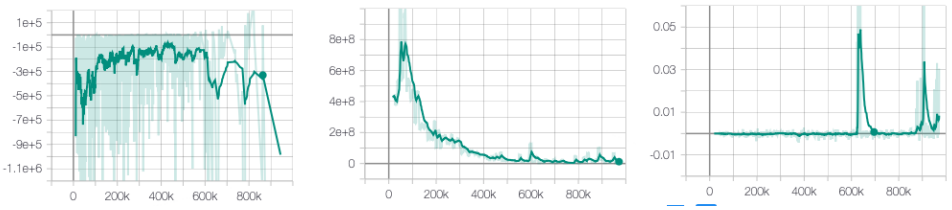


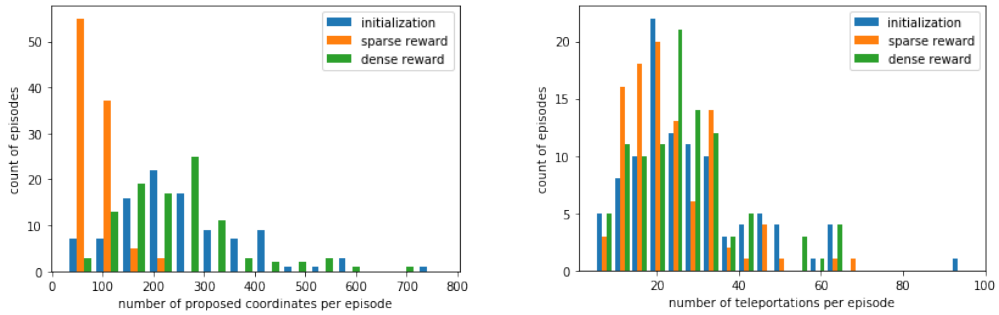
Figure 8: Training for dense reward based global policy: (a) Episode reward. (b) value function loss. (c) policy gradient loss.

To analyze both the policy variants, we evaluate the performance in terms of the number of proposed coordinates and the number of coordinates that are indeed used for teleportation. Note that we consider the policies after 2 million timesteps of training, and a better comparison could be between the best policy checkpoints of both the variants. Figure 9a shows that the sparse reward based policy uses fewer coordinates across episodes with most values as less than 150 timesteps, whereas the dense reward based policy is comparable to random initialization. In figure 9b, the number of coordinates used for teleportation for sparse reward based policy is lesser than the dense variant and random initialization. Note that the model was not trained to minimize the number of coordinates used to teleport, but its decrease is correlated with decrease in the overall proposed coordinates.

6 Discussion

The current approach to train the global policy involves continuous space of predictions to correspond to the coordinates. This could be made simpler in discrete action space where the model learns to predict the direction in which the nearest frontier should be explored. However, we would be relying on a strong assumption that nearest frontiers are the ones to be selected for good map coverage, but that is not true as in a limited budget to teleport, the nearest frontier within the current room might be a poor choice than an opening leading to an another room. We did not study how to represent the action space for learning global policy efficiently and believe it to be an open question.

To provide a warm start, the global policy can be pre-trained in a supervised manner. Unlike random initialization, this will ensure that the agent reaches the sparse reward through complete exploration



(a) the number of coordinates proposed per episode (b) the number of coordinates used for teleportation

Figure 9: Histograms to compare variants of global policy over 100 episodes for evaluation. The policy that proposes lesser number of coordinates and uses lesser steps to teleport is better.

of the environment. Though we did study the policies for behavior cloning of the expert trajectories in this coverage task, we did not succeed in pre-training the global policy network using imitation learning and then using reinforcement learning to fine-tune. This poses considerable challenge in on-policy algorithms like PPO considered for training local and global policy. Though off-policy algorithms would better accommodate the trajectories in the replay buffer, it should used with importance sampling to tackle the problem of overestimation of the value function. Given a diverse dataset of such frontiers in a map, we could train a global policy that could imitate such frontier selections. These demonstrations can be used to train a neural network to output the frontier that will be selected. In our case, this network is trained to find the nearest feasible frontier for exploration. We consider training this global policy in a supervised manner first. We hope to extend this to a reinforcement learning based policy that learns to provide feasible frontier locations in the map that can maximize time constrained map exploration as a reward.

The next steps are the integration of the global and the local policy to train end-to-end reinforcement learning model for navigation in partially observed environments. We propose to test this setup with different reward signals for obtaining diverse exploration behaviors. If the reward structure is dense, i.e. based on the euclidean distance to the subgoal, this should train the global policy network to increase the likelihood of the frontiers leading to the goal. Alternately, if the reward structure is based on the total explored area, while penalizing the number of steps, the policy/frontier selection network should learn to predict frontiers that efficiently increase map information. Therefore, we can showcase how this change could lead to diverse exploration and navigation behaviors.

Learning can improve frontier selection by incorporating the environment's structure and semantics. Apart from learning from human behavior, learning based approach to selecting the frontiers can be useful to learn the structure of the environment. For example, among different indoor environment, the semantic proximity of objects in the kitchen and the objects in washroom still holds. If the robot is tasked to fetch something from refrigerator, it will select frontiers which have a high probability to reach the kitchen or dining area.

7 Conclusion

We presented a hierarchical decomposition for learning navigation in partially observed environments as: (1) local policy for learning goal-conditioned navigation (2) global policy for learning strategic selection of coordinates for the tasks like coverage of the map. We have evaluated both the components in `FourRooms` environment with randomization in terms of position of room openings and agent position for both global and local policy. We also randomize the goal positions, and the submaps for the environment for training the local policy. We have demonstrated the performance of goal-conditioned local policy with curriculum based randomization introduced during training. We also show the global policy's performance with sparse reward and compare with a dense reward variant.

Acknowledgments

If a paper is accepted, the final camera-ready version will (and probably should) include acknowledgments. All acknowledgments go at the end of the paper, including thanks to reviewers who gave useful comments, to colleagues who contributed to the ideas, and to funding agencies and corporate sponsors that provided financial support.

References

[1] B. Yamauchi. A frontier-based approach for autonomous exploration. In *Proceedings 1997 IEEE International Symposium on Computational Intelligence in Robotics and Automation CIRA'97. 'Towards New Computational Principles for Robotics and Automation'*, pages 146–151, 1997.

[2] C. Stachniss, D. Hahnel, and W. Burgard. Exploration with active loop-closing for fastslam. In *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566)*, volume 2, pages 1505–1510 vol.2, 2004.

[3] A. Dai, M. Nießner, M. Zollöfer, S. Izadi, and C. Theobalt. Bundlefusion: Real-time globally consistent 3d reconstruction using on-the-fly surface re-integration. *ACM Transactions on Graphics 2017 (TOG)*, 2017.

[4] M. Bloesch, J. Czarnowski, R. Clark, S. Leutenegger, and A. Davison. Codeslam - learning a compact, optimisable representation for dense visual slam. pages 2560–2568, 06 2018. doi: 10.1109/CVPR.2018.00271.

[5] W. Yang, X. Wang, A. Farhadi, A. Gupta, and R. Mottaghi. Visual semantic navigation using scene priors. In *ICLR*, 2019.

[6] T. Chen, S. Gupta, and A. Gupta. Learning exploration policies for navigation. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=SyMWn05F7.

[7] G. J. Stein, C. Bradley, and N. Roy. Learning over subgoals for efficient navigation of structured, unknown environments. In A. Billard, A. Dragan, J. Peters, and J. Morimoto, editors, *Proceedings of The 2nd Conference on Robot Learning*, volume 87 of *Proceedings of Machine Learning Research*, pages 213–222. PMLR, 29–31 Oct 2018. URL http://proceedings.mlr.press/v87/stein18a.html.

[8] T. D. Kulkarni, K. R. Narasimhan, A. Saeedi, and J. B. Tenenbaum. Hierarchical deep reinforcement learning: Integrating temporal abstraction and intrinsic motivation. In *Proceedings of the 30th International Conference on Neural Information Processing Systems*, NIPS'16, page 3682–3690, Red Hook, NY, USA, 2016. Curran Associates Inc. ISBN 9781510838819.

[9] M. Al-Shedivat, L. Lee, R. Salakhutdinov, and E. P. Xing. On the complexity of exploration in goal-driven navigation. *CoRR*, abs/1811.06889, 2018. URL http://arxiv.org/abs/1811.06889.

[10] M. Chevalier-Boisvert, L. Willems, and S. Pal. Minimalistic gridworld environment for openai gym. https://github.com/maximecb/gym-minigrid, 2018.

[11] A. Das, S. Datta, G. Gkioxari, S. Lee, D. Parikh, and D. Batra. Embodied Question Answering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018.

[12] D. S. Chaplot, D. Gandhi, S. Gupta, A. Gupta, and R. Salakhutdinov. Learning to explore using active neural slam. In *International Conference on Learning Representations*, 2020. URL https://openreview.net/forum?id=HklXn1BKDH.

[13] B. Eysenbach, R. Salakhutdinov, and S. Levine. Search on the replay buffer: Bridging planning and reinforcement learning. *CoRR*, abs/1906.05253, 2019. URL http://arxiv.org/abs/1906.05253.

[14] A. Tamar, S. Levine, and P. Abbeel. Value iteration networks. *CoRR*, abs/1602.02867, 2016. URL http://arxiv.org/abs/1602.02867.

[15] L. Lee, E. Parisotto, D. S. Chaplot, E. P. Xing, and R. Salakhutdinov. Gated path planning networks. *CoRR*, abs/1806.06408, 2018. URL http://arxiv.org/abs/1806.06408.

[16] A. Goyal, R. Islam, D. Strouse, Z. Ahmed, H. Larochelle, M. Botvinick, S. Levine, and Y. Bengio. Transfer and exploration via the information bottleneck. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=rJg8yhAqKm.