RECON: Rapid Exploration for Open-World Navigation with Latent Goal Models

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Abstract—We describe a robotic learning system for autonomous navigation in diverse environments. At the core of our method are two components: (i) a non-parametric map that reflects the connectivity of the environment but does not require geometric reconstruction or localization, and (ii) a latent variable model of distances and actions for efficiently constructing and traversing this map. Trained on a large dataset of prior experience, this model predicts the expected amount of time needed to transit between the current image and a goal image, as well as the current action to take to do so. This model acquires a representation of goal images that is robust to distracting information. We demonstrate our method on a mobile ground robot in outdoor navigation scenarios. Given an image of a goal that is up to 80 meters away, our method learns to reach the goal in 20 minutes, and can reliably revisit these goals when faced with previously-unseen obstacles and weather conditions.

I. INTRODUCTION

Outdoor navigation in diverse environments demands a high degree of robustness and generalization, requiring that robots handle both visual variation (e.g., changes in lighting and appearance) and physical complexity (e.g., obstacles, difficult terrain). Different environments typically exhibit similar physical structures, and these similarities can be used to accelerating learning in new environments. Learning-based methods provide an appealing approach for learning a representation of this shared structure using prior experience. Since prior experience alone is not sufficient to determine the location of every object in a new environment, a successful navigation system must actively collect some experience in the new environment.

In this work, we consider the problem of navigating to a user-specified goal in a new environment. The robot has access to a large and diverse dataset of experience from other environments, which it can use to learn general navigational affordances. Our approach to this problem combines a goal-conditioned model with non-parametric memory. Learned from prior data, the goal-conditioned model encodes prior knowledge about perception, navigational affordances, and short-horizon control. The non-parametric memory incorporates experience from the new environment. Combined, these components enable our system to learn to navigate to goals in a new environment after only a few minutes of exploration.

The primary contribution of this work is a method for learning to navigate to goals in new environments. This method operates directly on a stream of image observations, without relying on structured sensors or geometric maps. Our method combines experience from prior environments with experience in the new environment into a semi-parametric map. An important part of our method is a compressed representation of goal images. This representation simultaneously affords robustness while providing a simple mechanism for exploration. This makes it possible, for example, to specify a goal image at one time of day, and then navigate to that same place at a different time of day: although the resulting observation differs considerably, the latent goal representation is sufficiently close that the model can produce the correct actions. Robustness of this kind is critical in real-world settings, where the appearance of

Fig. 1: RECON is a robotic learning system that can rapidly explore a new environment to reach a visually-specified goal, using a learned model trained in many previous environments. Given a goal image (a), RECON explores the environment (b) by sampling prospective latent goals and constructing a topological map (white dots), using only image observations and without explicit geometric mapping or localization. After finding the goal, (c) RECON can reuse the map to revisit the goal, as well as other states in the environment, much more rapidly (red path in (b)). (d) RECON uses data collected from diverse training environments to learn navigational priors that (e) enable RECON to quickly explore and learn to reach visual goals a variety of unseen environments.

Fig. 2: We demonstrate RECON on a Clearpath Jackal.
similar landmarks can change significantly with times of day and seasons of the year.

We demonstrate our method, Rapid Exploration Controllers for Outcome-driven Navigation (RECON), on a ground robot (Fig. 2) in open-world environments (Fig. 1). In our experiments, no more than 20 minutes of experience in each of 8 new environments enabled our method to discover user-specified image goals up to 80 meters away. Afterwards, our method can navigate to these goals in the presence of visual distractors and dynamic obstacles.

II. RELATED WORK

Exploring a new environment is often framed as the problem of efficient mapping, and posed in terms of information maximization: devising information-theoretic objectives for mapping and planning that guide the robot to uncertain regions of the environment. To do this, some prior methods use local strategies for generating control actions for the robots [1–4], or use global strategies that employ a variant of the frontier method [5–7]. However, building high-fidelity geometric maps of the environment, as these methods aim to do, can be hard without reliable depth information. Moreover, such maps cannot be used to reason about settings where traversability depends on non-geometric properties of the environment (e.g., tall grass is traversable, but a wire fence is not). Our method is structurally similar to [8, 9], which uses a two-stage planning approach using a global plan and local primitives for control. However, following the work of [1], our map is not geometric, but rather topological: it represents connectivity between landmarks observed through the robot’s camera, without attempting to explicitly reconstruct geometry. Similar to prior work [10–14], we construct this topological map by learning a distance function to estimate the time to transit between states, as well as a low-level policy for navigating between nearby states. Like prior work [10, 13], we will estimate distances via supervised regression and learn a local control policy via goal-conditioned behavior cloning. However, these prior methods do not describe how to learn to navigate in new, unseen environments. We will modify these prior methods by equipping them with an explicit mechanism for exploring in new environments and transferring knowledge across environments.

Exploration is also well-studied in the domain of reinforcement learning (RL). Many popular methods for exploration in RL algorithms involve a novelty-based exploration bonus. This exploration bonus is computed using the error of a predictive model [15–20], information gain [21, 22], or methods based on counts, densities, or distance from previously-visited states [23–25]. While these methods can yield state-of-the-art results in simulated domains, they often come at the cost of high sample complexity. Intuitively, these methods learn to reason about the novelty of a state only after visiting it. Instead, our approach is closely related to methods such as $E^3$ and HOMER [26, 27] that explicitly reason about which states are known, and which states are unknown.

One important capability of our method, using experience from one environment to accelerate learning in a new environment, has been extensively studied in the context of meta-learning [28–30], and transfer learning [31–35]. To do this, our method will use an information bottleneck [36], which will serve a dual purpose. First, as shown in prior work, the information bottleneck provides a representation that can aid the generalization capabilities of RL algorithms [37, 38]. Secondly, the information bottleneck is a measure of task-relevant uncertainty [39], so we can therefore use it to incorporate prior information for proposing goals that are functionally-relevant for learning control policies in the new environment.

The problem of learning goal-directed behavior has been studied extensively in prior work. Common learning-based approaches include goal-conditioned reinforcement learning [40–43] and goal-conditioned imitation learning [44–49]. Our build will build upon prior goal-conditioned imitation learning methods to solve a slightly different problem: how to reach goals in a new environment. Once placed in a new environment, our method will explore by carefully choosing which goals to command, a recipe used in prior work [50–54]. Unlike these prior methods, our method will make use of data from previous experiments in different environments to accelerate learning in the new environment.

III. PROBLEM ASSUMPTIONS AND SYSTEM OVERVIEW

We consider the problem of goal-directed exploration for visual navigation: a robot is tasked with navigating to a goal location $G$ in a new environment, given an image observation $o_g$ taken at $G$. We model the task of navigation as a Markov decision process with time-indexed states $s_t \in S$ and actions $a_t \in A$. We do not assume the robot has access to spatial localization or a map of the environment, or access to the environment, has been extensively studied in the context of meta-learning [28–30], and transfer learning [31–35]. To do this, our method will use an information bottleneck [36], which will serve a dual purpose. First, as shown in prior work, the information bottleneck provides a representation that can aid the generalization capabilities of RL algorithms [37, 38]. Secondly, the information bottleneck is a measure of task-relevant uncertainty [39], so we can therefore use it to incorporate prior information for proposing goals that are functionally-relevant for learning control policies in the new environment.

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We implement RECON on a Clearpath Jackal UGV platform (see Fig. 1). The default sensor suite consists of a 6-DoF IMU, a GPS unit for approximate global position estimates, and wheel encoders to estimate local odometry. In addition, we added a forward-facing 170◦ field-of-view RGB camera and an RPLIDAR 2D laser scanner. Inside the Jackal is an NVIDIA Jetson TX2 computer. The GPS and laser scanner can become
unreliable in some environments, so we use them solely as safety mechanisms during data collection – our method operates only using images taken from the onboard RGB camera, without other sensors or ground-truth localization.

B. Data Collection & Labeling

Our aim is to leverage data collected in a wide range of different environments to enable the robot to discover and learn to navigate to novel goals in novel environments. Intuitively, this data should allow our method to learn a prior over the general structure of environments. To demonstrate this capability, we run our core experiments using data exclusively from prior work [13, 55], which also used a Clearpath Jackal robot. This data consists of self-supervised trajectories collected by time-correlated random walks, and was collected over a span of 18 months and exhibits significant variation in appearance due to seasonal and lighting changes (see Fig. 1 (d)).

IV. RECON for Goal-Directed Exploration

Recall that our objective is to design a robotic system that uses a visual sensor to efficiently discover and reliably reach a target image in a previously unseen environment. Since the robot does not have a map or any experience in this environment, our system creates a topological map in this environment on the fly, by using the learned distance model to evaluate the expected number of time steps needed to transit between the different observations collected during exploration, which we refer to as temporal distance. RECON consists of two components that enable it to explore new environments. The first component is an uncertainty-aware, context-conditioned representation of goals that can quickly adapt to novel scenes. Critically, the goal representation is designed to be predictive of both the next action to take towards the goal as well as the temporal distance from the current observation to the goal observation. This representation provides a powerful mechanism for selecting exploration goals, as it gives the robot a target to explore, an estimated distance to the target (i.e., a distance prediction), and an estimated action (i.e., a policy) to help the robot approach the target. Our design of this first component results in a prior whose samples represent “imaginary” (latent) goals relative to the current observation. This property is leveraged by our system to produce meaningful exploration from any given location, which we show in our experiments is substantially more effective than exploring with random actions. The second component is a topological map constructed incrementally from frontier-based exploration. This map is used to increase the range of the robot while maintaining a compact memory of the target environment. Edges in the topological map are constructed using the distance predictions from the first component.

A. Learning to Represent Goals

Following prior work [10, 13, 14], we aim to learn our distance function and policy using an offline dataset of transitions collected from previous experience. In order for our model to use image inputs to compactly represent (i) goals, (ii) how to achieve goals, and (iii) relative distances to goals, we use an information bottleneck architecture [39, 56, 57]. We use a context-conditioned representation of goals [38, 58, 59] to learn a control policy in the target environment (Fig. 3 describes our graphical model). Letting $I(\cdot; \cdot)$ denote mutual information, the objective in Eq. 1 encourages the model to compress incoming goal images $o_t$ into a representation $z_t^g$ that is predictive of the action $a_t^g$ taken towards the goal, and the temporal distance from the current image $d_t^g$ (using upper-case to denote random variables):

$$I(A_t^g, D_t^g; Z_t^g | o_t) - \beta I(Z_t^g ; O_g | o_t) \tag{1}$$

Sampling this representation from a prior, as our exploration algorithm does, provides the robot with a waypoint towards which it should take an action, associated with a predicted temporal distance. Constructing our model in this way, such that the representations are relative to the current observation (context) enables the model to represent feasible goals. If, instead, the bottleneck was that of a typical VAE, in which the input images are autoencoded, then samples from the prior over these representations generally would not represent goals that are reachable from the robot’s current state. This distinction is crucial when exploring new environments, where most states from the training environments are not valid goals.

Following [39], we approximate the intractable objective in Eq. 1 with a variational posterior and decoder, in our case $p_\phi(z_t^g | o_g, o_t)$ and $q_\psi(a_t^g, d_t^g | z_t^g, o_t)$, respectively. The learning objective for the parameters of the posterior and decoder, given data $D$, results in the maximization objective:

$$L(\theta, \phi; D, \beta) = \frac{1}{|D|} \sum_{(o_t, o_g, a_t^g, d_t^g) \in D} \mathbb{E}_{p_\phi(z_t^g | o_g, o_t)} \left[ \log q_\psi(a_t^g, d_t^g | z_t^g, o_t) \right] - \beta \text{KL}(p_\phi(\cdot | o_g, o_t) || r(\cdot)) \tag{2}$$

where we define the prior $r(z_t^g) \triangleq \mathcal{N}(0, I)$. The first term measures the model’s ability to predict actions and distances from the encoded representation, and the second term measures the model’s compression of incoming goal images.
B. Goal-Directed Exploration with Topological Memory

The second component of our system is a topological memory of images. This topological memory is constructed incrementally as the robot explores a new environment, serving to provide an estimate of the exploration frontier as well as a map that the robot can use to later navigate efficiently to goals.

We describe our algorithm for exploring with this graph next, with accompanying pseudocode given in Alg. 1. To expand this memory, the robot uses the model from the previous section to propose subgoals for data collection. Given a subgoal, Alg. 1 proceeds by executing actions towards the subgoal for a fixed number of timesteps (Alg. 1 L12). The data collected during subgoal navigation expands the topological memory (Alg. 1 L14) and is used to fine-tune the model (Alg. 1 L15).

Thus, the task of efficient exploration is reduced to the task of choosing subgoals (Alg. 1 L14) and is used to fine-tune the model (Alg. 1 L15). The robot’s current estimate of the task goal reachability, as well as its proximity to the frontier of the graph. To determine the frontier, we keep track of the number of times each node in the graph was selected as the navigation goal (see Alg. 2, L8). This count roughly represents how often a previously memorized node was used for exploration, and nodes with low counts are considered to be on the frontier. In the following, we use $z^g_t$, $d^g_t$, and $d^d_t$ to denote the mean of the decoder $p_{θ}(z | o_t, o_g)$, and $d^d_t$ to denote the distance component of the mean of the decoder $q_{θ}(a_t, d_t | z^g_t, o_t)$ (i.e., the predicted number of time steps needed to transit from $o_t$ to $z^g_t$). The choice of subgoal at each step is made as follows:

(i) The robot believes it can likely reach the overall goal – it adopts the representation of the goal image as the subgoal (Alg. 1 L7). The robot’s confidence about its ability to reach the overall goal is based on the probability of the current goal embedding, $z^g_t$, under the prior $r(z)$. If $r(z^g_t)$ is large (above some threshold $ϵ$), it means that the relationship between the current observation $o_t$ and the goal $o_g$ is in-distribution, which suggests that the model’s estimates of the distance and action is reliable – intuitively, this means that the model believes that it knows how to reach $o_g$ from $o_t$.

(ii) The robot is at the least-explored node (frontier) – it adopts an unexplored subgoal relative to this node (Alg. 1 L9), by sampling a random relative subgoal $z^v_t$ from the prior. The robot determines whether it is at the frontier based on the distance (as estimated by the model) to its “least explored neighbor” – the node in the graph within a distance threshold ($δ_2$) of the current observation that has the lowest visitation count. If the distance to this node is low (lower than some threshold $δ_1$), then the robot is on the frontier.

(iii) The robot is not at the least-explored node – it adopts its “least-explored neighbor” as a subgoal (Alg. 1 L11), and navigates toward it using the action obtained from the model.

The SubgoalNavigate function rolls out the learned policy to navigate to the desired subgoal latent $z^v_t$, by querying the decoder $q_{θ}(a_t, d_t | z^w_t, o_t)$ in an open loop manner. The endpoint of such a rollout is used to update the visitation counts $v$ in the graph $G$ using the AssociateToVertex subroutine. To nudge the robot to the frontier, we use a heuristic LeastExploredNeighbor routine that uses the visitation counts of the neighbors to identify unexplored areas in the local neighborhood. At the end of each trajectory, the ExpandGraph subroutine is used to update the edge and node sets $\{E, V\}$ of the graph $G$ to update the non-parametric representation of the environment. Pseudocode for these subroutines are given in Alg. 2.

Algorithm 1 RECON for Exploration: RECON takes as input an encoder $p_{φ}(z | o_t, o_g)$, a decoder $q_{θ}(a_t, d_t | z^g_t, o_t)$, prior $r(z)$, the starting observation $o_t$ and goal observation $o_g$, $δ_1, δ_2, ϵ, γ, H$ are hyperparameters.

```
1: function RECON($q_{θ}, p_{φ}, r, o_t, o_g; β, δ_1, δ_2, ϵ, γ, H$)
2:     $G ← \emptyset, D ← \emptyset$ ▷ Initialize graph and data
3:     while $d^g_t < δ_1$ do ▷ Continue while not at goal
4:         $o_n ← $ LeastExploredNeighbor($G, o_t; δ_2$)
5:         $z^g_t ∼ p_{φ}(z | o_t, o_g)$ ▷ Encode relative goal
6:         if $r(z^g_t) > ϵ$ then
7:             $z^w_t ← z^g_t$ ▷ Will go to feasible goal
8:             else if $d^d_t < δ_1$ then
9:                 $z^v_t ∼ r(z)$ ▷ Will explore from frontier
10:            else
11:                $z^w_t ∼ p_{φ}(z | o_t, o_n)$ ▷ Will go to frontier
12:                $D_w, o_t ← $ SubgoalNavigate($z^w_t, H$)
13:                $D ← D ∪ D_w$
14:                ExpandGraph($G, o_t$)
15:                $L(φ, θ; D, β)$ for $γ$ epochs ▷ Eq. 2
16:         return model $p_{φ}, q_{θ}$ and memory $G$
```

Table I: Hyperparameters of Alg. 1.

| Hyperparam. | Value | Meaning |
|-------------|-------|---------|
| $δ_1$       | 4     | Temporal distance threshold of identification |
| $δ_2$       | 15    | Temporal distance threshold of neighbors |
| $ϵ$         | $10^{-2}$ | Threshold of exploration on prior |
| $β$         | 1.0   | Model complexity hyperparameter |
| $γ$         | 10    | Epochs to finetune model |
| $H$         | 5 seconds | Time to navigate to subgoal |

C. Implementation Details

Inputs to the encoder $p_{φ}$ are pairs of observations of the environment – current and goal – represented by a stack of two RGB images obtained from the onboard camera at a resolution of $160 × 120$ pixels. $p_{φ}$ is implemented by a MobileNet encoder [60] followed by a fully-connected layer projecting the 1024-dimensional latents to a stochastic, context-conditioned representation $z^g_t$ of the goal that uses 64-dimensions each
Algorithm 2 Pseudocode for subroutines referenced in the exploration algorithm shown in Alg. 1

1: function SubgoalNavigate($z^w; H$)
2:     trajectory ← ()
3:     for $t \in [1, \ldots, H]$ do
4:         trajectory.append(($o_t, a_t, t$))  # Sample action
5:         $o_t \leftarrow \text{Env.step} (a_t)$  # Execute action
6:     $v_H \leftarrow \text{AssociateToVertex}(G, o_H)$
7:     $v_H.\text{count} \leftarrow v_H.\text{count} + 1$
8:     $D_w \leftarrow ((o_t, o_H, a_t, H - t) \mid (o_t, a_t, t) \in \text{trajectory})$
9:     return $D_w, o_H$

1: function AssociateToVertex($G = (V, E), o_t$)
2:     $d \leftarrow \text{sort}([d^2_v; v \in V])$  # Predict distances
3:     $v, d \leftarrow d[0]$  # Associate $o_t$ with nearest vertex
4:     return $v$

1: function LeastExploredNeighbor($G = (V, E), o_t$)
2:     $\mathcal{V}_n \leftarrow \{v' : E(v, v') < 2, v' \in V\}$  # Retrieve neighbors
3:     $c \leftarrow \text{sort}((v'.\text{count}, v'.a) \mid v' \in \mathcal{V}_n)$  # Retrieve neighbor with smallest count
4:     $v_c, o_c \leftarrow c[0]$  # Retrieve neighbor with smallest count
5:     return $o_c$

1: procedure ExpandGraph($G = (V, E), o_t$)
2:     $v_t \leftarrow \text{Node} (\text{count} = 1, o = o_t)$  # Create node for $o_t$
3:     $E \leftarrow E \cup \{(v_t, v_g) : d^2_v, g \in V\}$  # Add edges
4:     $V \leftarrow V \cup \{v_t\}$  # Add vertex

Algorithm 3 RECON for Goal-Reaching: After discovering a path to the goal, RECON uses the topological graph $G$ to quickly navigate towards a goal observation $o_g$.

1: procedure GoalNavigate($G, o_t, o_g; H$)
2:     $v_t \leftarrow \text{AssociateToVertex}(G, o_t)$
3:     $v_g \leftarrow \text{AssociateToVertex}(G, o_g)$
4:     $(v_1, \ldots, v_g) \leftarrow \text{ShortestPath} (G, v_t, v_g)$
5:     for $v \in (v_1, \ldots, v_g)$ do
6:         $z \leftarrow p_\phi (z \mid o_t, o_g = v, o)$
7:     $D_w, o_t \leftarrow \text{SubgoalNavigate} (z; H)$

### Table II: Architectural Details of RECON

The inputs to the model are RGB images $o_t \in [0, 1]^{3 \times 160 \times 120}$ and $o_g \in [0, 1]^{3 \times 160 \times 120}$, representing the current and goal image. The model processes images with MobileNet encoders [60].

| Layer Number | Input [Dimensionality] | Output [Dimensionality] | Layer Details |
|--------------|------------------------|------------------------|--------------|
| 1            | $o_t [3, 160, 120]$, $o_g [3, 160, 120]$ | $I^1_p [6, 160, 120]$ | Concatenate images along channel dimension. |
| 2            | $I^1_p [6, 160, 120]$ | $E^1_p [1024]$ | MobileNet Encoder [60] |
| 3            | $E^1_p [1024]$ | $\mu_p [64], \sigma_p [64]$ | Fully-Connected Layer, exp activation of $\sigma_p$ |
| 4            | $\sigma_p [64]$ | $\sigma_p [64]$ | torch.diag($\sigma_p$) |

### D. Algorithm Summary

Combining the latent goal model with the topological graph, RECON can quickly discover user-specified goals in new environments and navigate to them reliably. Our full method consists of three stages:

1) **Prior Experience**: The goal-conditioned distance and action model is trained using experience from previously visited environments. Supervision for training our model is obtained by using time steps as a proxy for distances and a relabeling scheme described in prior work [13]. This data is described in Sec. III-B.

2) **Exploring a Novel Environment**: When dropped in a new environment, RECON uses a combination of frontier-based exploration and latent goal-sampling with the learned model to discover a visual target. The learned model is also finetuned to the new environment. These steps are summarized in Alg. 1.

3) **Navigating an Explored Environment**: Given an explored environment (represented by a topological graph $G$) and the model, RECON uses $G$ to navigate to a goal image by planning a path of subgoals through the graph. This process is summarized in Alg. 3.

### V. Experimental Evaluation

We designed our experiments to answer four questions:

**Q1.** How does RECON compare to current methods for the task of visual goal discovery in novel environments?
Fig. 4: Exploring and Learning to Reach Goals: (left) Amount of time needed for each method to search for the goals in a new environment (↓ is better; hashed out bars represent failure). (right) Amount of time needed to reach the goal a second time, after reaching the goal once and constructing the map, in seconds (↓ is better).

Fig. 5: Goal-Reaching Behavior of RECON and Baselines: (left) We visualize some example trajectories to goals discovered by RECON in previously unseen environments. RECON can discover paths to visually-specified goal in a diverse set of environments and quickly navigate to them in future trials. (right) After exploration, we visualize the goal-reaching policy learned by RECON and the baseline methods. Only RECON and the RECON-RA baseline have learned how to reach the goal successfully, and RECON takes the shorter route.

| Method    | Exploration Time (mm:ss) | Recovered Path (mm:ss) |
|-----------|--------------------------|------------------------|
| RECON     | 09:54                    | 00:26                  |
| RECON-RA  | 14:54                    | 00:31                  |
| InfoBot   | 23:36                    | 00:48                  |
| PPO-RND   | 21:18                    | 00:47                  |
| ViNG      | 19:48                    | 00:34                  |

Q2. After discovering the goal the first time, is RECON able to navigate to the goal again much more quickly, by leveraging its experience and non-parametric memory?
Q3. Can RECON robustly discover goals in non-stationary environments, in the presence of appearance changes and novel obstacles?
Q4. How important are the various components of RECON, such as sampling from an information bottleneck and non-parametric memory, to its performance, and how does it compare to alternative designs, including those proposed in prior work?

A. Goal-Directed Exploration in Novel Environments

We perform our evaluation in a diverse variety of outdoor environments shown in Fig. 1, including parking lots, suburban housing, sidewalks, and cafeterias. We train on prior data, described in Sec. III-B, in a subset of these environments by maximizing Eq 2, and evaluate our system’s ability to discover user-specified goals, indicated as an RGB image, in previously unseen environments.

We evaluate RECON against three baselines trained on offline data:
- RECON-RA: a variant of our method that executes random action sequences at the frontier, rather than perform-
Exploring Non-stationary Environments: RECON plans over a compressed representation that ignores distractors in the environment, while the learned policy is reactive. It can explore a non-stationary environment, successfully discovering and navigating to (a) the visually-specified goal. The learned representation and topological graph are robust to visual distractors, allowing RECON to reliably navigate to the goal under previously unseen obstacles (c–e) and a variety of lighting and weather conditions (f–h).

We evaluate the ability of RECON to discover visually-indicated goals in 8 unseen environments and navigate to them repeatedly. For each trial, we provide an RGB image of the desired target (one per environment) to each method and report: (i) the time taken by each method to discover the desired goal (Q1), and (ii) the time taken by each method to reliably revisit the discovered goal a second time using the map constructed during the first attempt (Q2). We show quantitative results in Fig. 4, and visualize RECON and baselines in Fig. 5.

Towards answering Q1, Fig. 4-a and Tab. III show that RECON outperforms all the baselines, discovering goals that are up to 80m away in under 20 minutes, including in settings where no other baseline can reach the goal successfully. RECON-RA and ViNG are able to discover the goal in all but the hardest environment, albeit taking up to 50% more time. We attribute RECON’s success to the context-conditioned sampling strategy (described in Sec. IV-A), which proposes goals that can aid the exploration of new environments. PPO-RND is able to discover goals that are up to 25m away, but fails to discover more distant goals. Off-InfoBot performs comparably to PPO-RND in the simpler environments, but fails to reach more distant goals, likely because using reinforcement learning for finetuning is data-inefficient. Indeed, prior work found that InfoBot requires upwards of 1M timesteps to adapt to new environments in simulation [38].

To answer Q2, we measure the time taken to reach the goal again, after the initial exploration trial. Fig. 4-b suggests that in addition to fast exploration, RECON variants and ViNG are also able to quickly recall a feasible path to the goal. RECON and ViNG create a compact topological map of its experience in the target environment which simplifies the navigation problem to a simple planning problem on the topological graph followed by short-horizon control, allowing it to quickly reach previously-seen states. PPO-RND and off-InfoBot are unsuccessful at recalling previously seen goals for all but the simplest environments. Fig. 5 shows an aerial view of the paths recalled by various methods in one of the environments – G. RECON and RECON-RA are successfully able to navigate to the checkerboard goal, while PPO-RND and off-Infobot result in collisions with obstacles in the environment; further, we notice that RECON discovers a shorter path to the goal and takes 20% lesser time to navigate than RECON-RA.

B. Exploring Non-Stationary Environments

Outdoor environments are often non-stationary and change over time: they contain dynamic obstacles such as automo-
biles and humans, and the appearance of the scene changes depending on the time of day and the season of the year. Successful exploration and navigation in such environments requires learning a representation that is invariant to such distractors. This capability is of central interest when using a non-parametric topological map: if we want the topological map to remain useful when new obstacles or lighting conditions are presented, we must ensure that the learned representation is invariant to such changes.

To test the robustness of RECON, we first had RECON explore in a new “junkyard” to learn to reach a goal image containing a blue dumpster (Fig. 6-a). Then, without any more exploration, we evaluated the learned goal-reaching policy when presented with previously unseen obstacles (trash cans, traffic cones, and a car) and and weather conditions (sunny, overcast, and twilight). Fig. 6 shows trajectories taken by the robot as it successfully navigates to the goal in scenarios with varying obstacles and lighting conditions. These results suggest that the learned representation of visual observations is invariant to visual distractors that do not affect robot’s decisions to reach a goal (e.g., changes in lighting conditions do not affect the trajectory to goal, and hence, are discarded by the bottleneck).

C. Dissecting RECON

RECON explores by sampling goals from the prior distribution over state-goal representations. To quantify the importance of this exploration strategy (Q4), we deploy RECON to perform undirected exploration in a novel target environment without building a graph of the environment. We compare the coverage of trajectories of the robot over 5 minutes when: (i) it performs rollouts towards sampled goals, and (ii) it executes random action sequences [20]. Fig. 7 shows the trajectories taken by the robot in these cases. We see that performing rollouts to sampled goals results in significantly better coverage than random action sequences, enabling faster exploration in novel environments.

We also evaluate several variants of RECON that ablate its goal sampling and non-parametric memory on the end-to-end task of visual goal discovery in novel environments:

- **Vanilla Sampling:** a variant of our method which learns a goal-conditioned policy and distances without an information bottleneck to obtain compressed representa-
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