Where are the Keys? – Learning Object-Centric Navigation Policies on Semantic Maps with Graph Convolutional Networks

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Abstract—Emerging object-based SLAM algorithms can build a graph representation of an environment comprising nodes for robot poses and object landmarks. However, while this map will contain static objects such as furniture or appliances, many moveable objects (e.g. the car keys, the glasses, or a magazine), are not suitable as landmarks and will not be part of the map due to their non-static nature. We show that Graph Convolutional Networks can learn navigation policies to find such unmapped objects by learning to exploit the hidden probabilistic model that governs where these objects appear in the environment. The learned policies can generalise to object classes unseen during training by using word vectors that express semantic similarity as representations for object nodes in the graph. Furthermore, we show that the policies generalise to unseen environments with only minimal loss of performance. We demonstrate that pre-training the policy network with a proxy task can significantly speed up learning, improving sample efficiency. Code for this paper is available at https://github.com/nikosuenderhauf/graphConvNetsForNavigation

I. INTRODUCTION

Where should a domestic service robot go look for the misplaced keys? Where would it find a bottle of milk, where would the owners have placed the remote control for the TV? Humans have an intuitive understanding of where to successfully search for these objects: The remote will most likely be found in the vicinity of the TV, the sofa, or the armchair. The milk will most likely be in the fridge, but maybe someone left it out on the kitchen table or the benchtop. In human-made environments, many – if not most – objects are not placed randomly, but tend to appear in proximity to a small set of other objects with related semantics or functionality. Humans have intuitive access to this underlying probabilistic process.

In this paper, we investigate if an agent can learn a navigation policy on a graph-based map comprised of pose nodes and static object landmarks (see Fig. 1 for an illustration). We show that a graph convolutional network can act as a policy network, providing a distribution over the pose nodes in the graph map. By training this network with reinforcement learning and sampling navigation goals from the resulting distribution, an agent can learn to find objects that do not appear in the map due to their non-static nature.

In contrast to recent work that learns to navigate directly from raw images, our approach learns on the graph maps constructed by an emerging family of object-based semantic SLAM systems [1]–[7]. While approaches learning from raw pixels typically take in the order of millions of episodes to train, our approach learns much faster, converging after a few 10,000 episodes. We present a method for pre-training based on a proxy task that speeds up the learning process even further.

As we will demonstrate, the learned policies can generalise to objects never encountered during training. This is possible because we use FastText word vectors [8] to represent object landmarks in the graph map. These vector representations have been trained on a large corpus of text data and capture semantic similarity between different words. If during deployment the target object is unknown (e.g. butter or yoghurt), but semantically similar to one of the known objects (e.g. milk), and it tends to appear in similar places (e.g. in the fridge or the kitchen table), the policy has a high chance of successfully navigating towards it within the given time budget. We also show that the policies are independent of the graph structure and layout, i.e. they generalise to unknown environments with only a minimal drop in performance.

II. RELATED WORK

1) Object-based Semantic Mapping and SLAM: Our research is motivated by the emerging body of work in se-


**III. Problem Description and Assumptions**

We propose an approach to learn a navigation policy that enables a robot to find small, non-static household objects such as keys, or glasses, within a domestic environment. We make the following assumptions that are reasonable for a domestic service robot application:

1. The robot has mapped the environment using an object-based semantic SLAM system such as [1] or others [2]–[7].
2. The available semantic map is a graph structure, with pose nodes and object landmark nodes. An edge between two pose nodes represents that the robot can navigate from one pose to the other. An edge between an object landmark and a pose indicates the object is in range for useful interaction.
3. Objects in the map are static and will therefore be furniture items or appliances such as table, bed, or fridge.
4. The objects of interest that need to be found by the robot are smaller, moveable objects that are not mapped due to their non-static nature, such as keys, glasses, cup, or remote.
5. These objects of interest appear in the vicinity of the mapped objects with a certain probability. E.g. a remote control will appear with some probability at the sofa, armchair, or TV, but never in the wardrobe or fridge.
6. The probabilistic model underlying this process is unknown and not directly accessible to the robot. Every time we evaluate the policy (and for every episode during training), the objects of interest are randomly placed in the environment (governed by the hidden probabilistic process).
7. The task of the policy is to find an object of interest. In the following, we will refer to these objects of interest as target objects. One policy should be capable of navigating to all target objects, i.e. we do not learn a target-specific policy.
8. The policy acts as a high-level planner, proposing to navigate to a pose node in the graph-based map. We assume that the robot has sufficient low-level navigation capabilities to reach this goal pose by a combination of path planning on the map and low-level motion control paired with reactive obstacle avoidance. We also assume the robot can localise itself with respect to the given map, building on the capabilities of current SLAM systems [1]–[7].

**IV. Approach**

We propose to learn a policy \(\pi(\mathcal{G}, c_{\text{target}})\) to find a target object of class \(c_{\text{target}}\) in an environment represented by a graph-based map \(\mathcal{G}\). As we explained in Section [III] the target object is not part of the map represented by \(\mathcal{G}\). Instead, the policy \(\pi\) needs to learn the hidden probabilistic model that governs the complex relationship between the mapped objects and potential target objects.

We implement \(\pi(\mathcal{G}, c_{\text{target}})\) as a neural network, consisting of a Graph Convolutional Layer [21] and fully connected layers. This network acts as a policy network, providing a distribution over the pose nodes in \(\mathcal{G}\), conditioned on \(c_{\text{target}}\). A navigation goal for the agent is selected by sampling from \(\pi(\mathcal{G}, c_{\text{target}})\). We train \(\pi\) with REINFORCE, a simple policy gradient method [27].

Current object-based semantic SLAM systems such as [1]–[7] assume a static environment and cannot use dynamic objects as landmarks.
A. Details of the Graph-based Map Representation $G$

The policy network $\pi(G, c_{\text{target}})$ operates on a graph-based map $G = (\mathcal{X} \cup \mathcal{L}, \mathcal{E})$ that comprises robot pose nodes $\mathcal{X}$, landmark nodes $\mathcal{L}$, and edges $\mathcal{E}$. Such a graph can be constructed easily from the outputs of a modern object-based SLAM system [1], [2]. We assume the robot poses $x_i \in \mathcal{X}$ are elements of $\text{SE}_3$. The landmarks $l_j \in \mathcal{L}$ comprise geometric information such as their pose and shape, and a class label $c_j \in \mathcal{C}_{\text{map}}$. The set $\mathcal{C}_{\text{map}}$ comprises all object classes that can be mapped by the semantic SLAM algorithm that constructs $G$. As explained in Section III this will be static objects such as furniture items and appliances.

The target object class $c_{\text{target}}$ will be from the set $\mathcal{C}_{\text{targets}}$ that contains non-static classes such as keys or glasses which will never appear as landmarks in the map $G$. We note that strictly $\mathcal{C}_{\text{map}} \cap \mathcal{C}_{\text{targets}} = \emptyset$ and also $c_{\text{target}} \notin \mathcal{C}_{\text{map}}$.

B. Augmenting the Graph Map with Word Vectors

We augment the graph by adding a semantic representation in the form of a vector $y_i$ to every node. It is these representations $y_i$ that the Graph Convolutional Layer in $\pi$ will operate on. For a landmark node $l_j$ with class label $c_j$, we use the FastText [8] word vector corresponding to $c_j$ as its semantic representation $y_j$. The FastText word vectors are continuous 300-dimensional representations and have been trained on a large corpus of text data comprising 16 billion tokens from Wikipedia, the UMBC webbase corpus and the statmt.org news dataset. These word vectors maintain semantic similarity: two words with similar meaning will have vector representations that have a small cosine distance [8].

Since pose nodes $x_i$ do not carry immediate semantic information, we initialise their respective semantic representation $y_i$ with $0 = (0, 0, \ldots, 0)^T$.

C. A Graph Convolutional Network as Policy Network

We implement the policy $\pi$ as a neural network consisting of one graph convolutional layer followed by three fully connected layers, with ReLu nonlinearities between all layers.

The graph convolutional layer implements the graph convolution operator proposed in [21]:

$$Z = \sigma(\mathbf{D}^{-\frac{1}{2}} \mathbf{A} \mathbf{D}^{-\frac{1}{2}} \mathbf{Y} \Theta)$$

where $\mathbf{Y} \in \mathbb{R}^{N \times 300}$ is the matrix of all node representations $y_i$, of dimensionality 300, $\Theta \in \mathbb{R}^{300 \times 64}$ is the weight matrix of the graph convolutional layer, and $\sigma$ is the element-wise ReLu function. $\mathbf{A} = \mathbf{A} + \mathbf{I}$ denotes the graph adjacency matrix $\mathbf{A}$ with inserted self-loops, and $\mathbf{D}_{ii} = \sum_j \mathbf{A}_{ij}$ is the diagonal degree matrix of the graph. For each node in the graph, operation (1) essentially accumulates the representations of all the node’s direct neighbours. It compresses the original 300-dimensional representations into a more compact 64-dimensional representation $z_i$. Fig. 2 illustrates the concept.

A network $f(z_i, z_{\text{target}})$ of three fully connected layers $f_1, f_2, f_3$ calculates the final output $p_i$ of the policy network for each node in the graph. The 64-dimensional representation of the target class is obtained by multiplying the word vector representation of the target $y_{\text{target}}$ with the parameters of the graph convolutional layer: $z_{\text{target}} = \sigma(y_{\text{target}} \cdot \Theta)$. Before passing it through the first layer $f_1$, $z_{\text{target}}$ gets concatenated with the representation of each node $z_i$. The input and output dimensionalities of the three layers is (128, 64), (64, 32), (32, 1) respectively.

The final output of the policy network $\pi(G, c_{\text{target}})$ is a vector $p$ with $p_i$ acting as the logits to a categorical probability distribution over all nodes in the graph. By sampling from that distribution, we obtain a navigation goal for the agent.

D. Training the Graph Convolutional Policy Network

We train the policy network $\pi(G, c_{\text{target}})$ with REINFORCE, a simple policy gradient method. We use Adam as optimiser and set the initial learning rate to $10^{-4}$. In order to obtain a reward, the agent has to find the target object

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2Without loss of generality for our proposed method they could also be elements of SE2 or even $\mathbb{R}^2$ (representing only position).

3Specifically, we used the pre-trained representations available in the `wiki-news-300d-1M.vec.zip` file from the FastText website [https://fasttext.cc/docs/en/english-vectors.html] (28) as the basis for our implementation.

4Empirically chosen. A comparative study on different network architectures or hyperparameters is beyond the scope of this paper.

5The described implementation does not distinguish between pose nodes and landmark nodes in the graph. Therefore, before sampling from the distribution $\pi$, we set the values of $p_i$ for all nodes corresponding to landmarks to $-100$, so that they are essentially never chosen as a goal.
within 10 time steps, i.e. it can only select 10 navigation goals before the episode ends. We assume the agent can always reach the selected goal and do not take the geodesic distance to the selected goal into account. Future work could also reward the shortest path length.

To obtain a robust evaluation, we train 10 agents for 50,000 episodes. For increased robustness and to show that the specifics of the probabilistic model $\mathcal{P}$ that governs the placement of target objects have no influence on the results, we repeat the training and evaluation in 20 environments with different underlying probabilistic models. Thus, in total we train 200 agents.

E. Constructing Graph Maps for Training and Evaluation

The graph maps used for training and evaluation are all constructed following the same principle: We first build the pose graph backbone, consisting of 1000 nodes and their connecting edges. Pose nodes are randomly assigned one of four room types from the set (kitchen, bedroom, living room, office). When a new pose node is inserted, it has a 95% chance of being of the same room type as its predecessor. After the pose graph backbone is built, we start populating the map with object landmarks. Every map contains between 100 and 500 objects from the set $\mathcal{L}$. For every object that is to be placed, we randomly choose a pose node to connect it to (the object will be “visible” from that pose). Depending on the room type of the pose node, the object class is drawn from one of 20 classes\(^7\). To simulate objects being visible from more than one pose, we keep connecting the landmark to the next pose node with 50% probability for each next pose, as long as the poses are of the same room type.

Target objects do not appear directly in the map. Instead, they spawn in the proximity of mapped objects with certain probabilities. This probabilistic process $\mathcal{P}$ is itself randomised in training and evaluation: the probability values are drawn from a uniform distribution between 0.1 and 0.9. However, target objects can only appear in the proximity of certain map objects\(^8\).

F. A Proxy Task for Pre-Training the Policy Network

The graph convolutional layer and the fully connected layers in the policy network $\pi$ can be effectively pre-trained by learning to solve a proxy task that does not require knowledge about the particular layout or structure of a map or the probabilistic model governing the object placement. For this proxy task we randomly generate maps and place objects from $\mathcal{L}^\text{map}$ and $\mathcal{L}^\text{targets}$ in it. It is important to understand that the object placement is not controlled by the same probabilistic model that is used to construct the graph maps for the actual navigation tasks. We then train the network to solve a classification task: given a class representation $y^\text{target}$, which pose nodes are connected to an instance of this class? We randomly sample a different target class for every minibatch and use a binary cross entropy loss function.

Pre-training on this proxy task initialises the weights in all network layers to values that are useful to interpret the semantic word vector representations. We demonstrate in Section VI-B that this speeds up the learning process for the actual navigation task we are interested in.

V. Evaluation

We evaluate all 200 trained agents on 1000 episodes each (100 randomly generated maps per agent, using 20 different probabilistic models $\mathcal{P}$ controlling the target object locations, and 10 randomly chosen target objects per map).

A. Baselines

We compare the learned policies against two baselines:

a) Random Policy: The random policy baseline chooses a random pose node in the graph as the navigation goal. It never chooses the same node twice.

b) Oracle Policy: The oracle policy has full access to the probabilistic model that controls where target objects appear in the environment. It can calculate the probability of finding the target object at any pose node, and chooses the node with the maximum probability as the navigation target. If the target object cannot be found there, it chooses the next likely goal and so on. It never chooses the same goal twice.

B. Performance Metrics

We use the following metrics to characterise performance:

a) Success Rate: How often can the agent find the target object within 10 time steps? I.e. the agent can navigate to 10 goal locations before the episode ends unsuccessfully.

b) Steps to Target: To how many goals does the agent navigate on average before it eventually finds the target object? Notice that this measure only incorporates successful episodes.

VI. Results

This section explains the four key results and insights gained from the conducted experiments.

A. Graph Convolutional Networks Can Successfully Learn Object-centric Navigation Policies on Semantic Maps

The left side of Table II compares the performance of two learned policies with the two baseline policies (random and oracle). As we can see, the policy networks successfully learned to find target objects in their training environments. The trained policies achieve almost perfect results, finding the target object after around 1.4 steps on average and successfully finishing 99% of the episodes in time (with
TABLE I: Performance of different policies on the training environments and novel environments not encountered in training.

| Policy          | Evaluate on Training Environment | Evaluate on Unseen Environments |
|-----------------|----------------------------------|---------------------------------|
| random          | success rate                     | steps to target                 |
| no pre-training | 0.33 ± 0.47                      | 5.00 ± 2.70                     |
| with            | 0.98 ± 0.13                      | 1.41 ± 1.03                     |
| pre-training    | 0.99 ± 0.09                      | 1.45 ± 1.09                     |
| oracle          | 0.99 ± 0.09                      | 1.66 ± 1.51                     |
| random          | success rate                     | steps to target                 |
| no pre-training | 0.26 ± 0.44                      | 5.10 ± 2.89                     |
| with            | 0.92 ± 0.28                      | 2.39 ± 2.07                     |
| pre-training    | 0.96 ± 0.20                      | 2.02 ± 1.78                     |
| oracle          | 0.99 ± 0.12                      | 1.62 ± 1.49                     |

TABLE II: Results on unseen environments with unseen target objects.

| Policy          | success | steps |
|-----------------|---------|-------|
| random          | 0.25 ± 0.43 | 5.14 ± 2.99 |
| no pre-training | 0.72 ± 0.45 | 3.16 ± 2.54 |
| with            | 0.76 ± 0.43 | 2.90 ± 2.44 |
| pre-training    | 0.97 ± 0.17 | 1.89 ± 1.78 |
| oracle          | 0.78 ± 0.17 | 2.07 ± 1.78 |

C. The Learned Policy Generalises to Unseen Environments

Table II compares the average performance of different policies when evaluated in their training environment and when transferred into a novel, unseen environment with different characteristics.

When transferred into unseen environments with new randomised probabilistic characteristics, the performance drops only slightly from 99% to 96% success rate and from 1.4 to 2.0 steps to target on average (from 98% to 92%, and from 1.4 to 2.39 steps without pre-training). Thus we can conclude that the learned policy (especially when initialised with proxy task pre-training), generalises well to unseen environments where the placement of potential target objects is controlled by a different hidden probabilistic model.

D. The Learned Policy Generalises to Unseen Classes

How well can the learned policies generalise to target classes that were never encountered during training (or pre-training)? To answer this question, we removed all known target objects and replaced them with unknown objects that are in most cases semantically similar to one of the known classes, and tend to appear in similar places.

As illustrated in Fig. 5, the policies generalise well. This performance is based on the expressive power of the FastText word vectors that capture semantic similarity. With the exception of the cellphone class that did not have a semantically similar class in the training dataset, the performance of both learned policies is much better than random, and close to the oracle policy. As before, agents using a policy network that was initialised with proxy task pre-training tend to perform better. Table [II] summarises the results.
**VII. Conclusions**

The recently emerging class of object-based semantic SLAM systems provide us with very compact, yet rich representations of the environment of mobile robots. Especially applications such as domestic service robotics and elderly care robotics can benefit from the graph-based maps that contain rich semantic information. However, more research into how the maps generated by this new class of SLAM systems can be used most beneficially is needed.

We contributed to this exciting new direction of research and demonstrated that a graph convolutional network is able to learn a navigation policy on such a graph. We have shown that word vectors are useful representations for landmark classes in this context, allowing the navigation policy to generalise to semantically similar, but previously unseen object categories. In future work we hope to evaluate this approach online on a robot, in concert with an object-based semantic SLAM system such as QuadricSLAM [1]. We have not yet studied the influence of various hyperparameters, the network architecture, or the word vector representation on the performance of the presented approach.
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