Graph Neural Networks for Learning Robot Team Coordination

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Abstract

This paper shows how Graph Neural Networks can be used for learning distributed coordination mechanisms in connected teams of robots. We capture the relational aspect of robot coordination by modeling the robot team as a graph, where each robot is a node, and edges represent communication links. During training, robots learn how to pass messages and update internal states, so that a target behavior is reached. As a proxy for more complex problems, this short paper considers the problem where each robot must locally estimate the algebraic connectivity of the team’s network topology.

1 Introduction

Robot teams are becoming a de-facto solution to many of today’s logistics problems (product delivery [Grippa et al., 2017], warehousing [Enright and Wurman, 2011], and mobility-on-demand [Pavone et al., 2012]). Robot teams also hold the promise of delivering robust performance in unstructured or extreme environments [Thayer et al., 2001, Kantor et al., 2003]. These applications hinge on algorithms that successfully and efficiently coordinate the robots, by providing solutions to collective decision-making, formation and coverage control, and task allocation problems.

This work focuses on the problem of developing distributed coordination mechanisms. To date, most distributed coordination algorithms tend to be point-solutions to very specific applications, and a lot of work goes into their design [Oh et al., 2015, Garin and Schenato, 2010, Rossi et al., 2018]. Notably, many state-of-the-art approaches rely on idealized and simplistic operational assumptions (e.g., reliability of inter-robot communications and robot homogeneity). Some of our recent work highlights the challenge of developing coordination mechanisms in heterogeneous or faulty robot teams [Prorok et al., 2017, Saulnier et al., 2017]: not only are these algorithms computationally hard, but also, they are difficult to design. As a consequence, we are interested in methods that more easily generate coordination mechanisms that are capable of functioning under complex operational conditions. Although some work has already been done in the domain of learning for robot team coordination [Liemhetcharat and Veloso, 2017, Amato et al., 2016], it is still a nascent field of research.

The goal of this paper is to apply a recent machine learning model, Graph Neural Networks (GNNs) [Scarselli et al., 2009], to the problem of robot team coordination. The GNN framework exploits the fact that many underlying relationships among data can be represented as graphs. Although GNNs have been applied to a number of problem domains, including molecular biology [Duvenaud et al., 2015], quantum chemistry [Gilmer et al., 2017], and simulation engines [Battaglia et al., 2016], they have yet to be considered within the multi-robot domain. Nevertheless, we have found that the fit is quite natural, as we capture the relational aspect of robot coordination by modeling the robot team as a graph, where each robot is a node, and edges represent communication. This representation allows us to exploit GNNs to learn the desired coordination mechanism, where we presume that examples of the target behaviors are given to the system in a supervised learning setting.

2 Problem and Method

In our problem setting, robot team coordination is broken down into two main parts, (i) inter-robot message exchange, and (ii) robot state update. The goal is to learn both these parts. In a first instance (within the context of this short paper), we consider a simple problem as a proxy for more complex problems: distributed computation of the connectivity of the robot team.

Our notation leans on the notation in [Gilmer et al., 2017]. We consider an undirected graph $G = (V, E)$ with edges $E$ and nodes $V$. Connected nodes can pass each other messages for a duration of $T$ time-steps. Neighbors of a node $v$ are denoted by $N(v)$. Messages are denoted by $m_v^t$ for node $v$ at time $t$. During the message passing phase, nodes update their internal states, $h_v^t$. These updates are defined through a message function $M_t$ and a node update function $U_t$: $m_v^{t+1} = \sum_{w \in N(v)} M_t(h_v^t, h_w^t, e_{vw})$, $h_v^{t+1} = U_t(h_v^t, m_v^{t+1})$ (1)

After messages have been passed, a local readout function $R_v$ returns a feature vector describing a node characteristic: $\hat{y}_v = R_v(h_v^T)$. We can also define a global readout function $\hat{y} = R(\{h_v^t | v \in G\})$ that is invariant to node permutations (graph isomorphisms). The key point is that the functions $M_t, U_t, R_v$ and
In this work, we distribute the computation of the algebraic connectivity of the network topology of a multi-robot team (with $|V|$ robots). In other words, each robot computes its own local estimate. In coordination mechanisms that rely on consensus, the algebraic connectivity is an important network property: it predicts convergence and characterizes the convergence rate. Notably, it is associated to the robustness of network topologies [Shahriar et al., 2015, Olfati-Saber and Murray, 2004], with recent work demonstrating its effect on robot team resilience [Saulnier et al., 2017]. The algebraic connectivity is computed by taking the second smallest eigenvalue of the graph Laplacian. Since global knowledge of the network topology is needed to compute the Laplacian, this is generally done in a centralized manner. Distributed algorithms that estimate the algebraic connectivity have previously been proposed [Aragues et al., 2012, Di Lorenzo and Barbarossa, 2014, Poonawala and Spong, 2015]. Although the details of the aforementioned estimation algorithms differ, they are all iterative approaches that lean on involved first-principles-based design.

Our approach is to bypass the principled design of these distributed algorithms, and to estimate the algebraic connectivity ($\lambda_2$) directly via a learned coordination mechanism. Briefly stated, each node $v$ in the system estimates a local value $\hat{\lambda}_{2,v}$ via the local readout function $R_v$:

$$\hat{\lambda}_{2,v} = R_v(h_v).$$

### 3 Experiments

We adapted an implementation of GNNs available on github [1]. Our message passing function is a linear transform of the state; the state update function is handled by a GRU and the readout functions consist of a single hidden layer. All hidden layers have size 100, and all activations are ReLUs. The GNN is trained for a duration $T \in \{2, 4, 8\}$, over 100 epochs, using Adam with a learning rate of $10^{-3}$. We implement two variant GNNs: a centralized model (with global readout), and a distributed model (with local readout). We generated 100'000 random training examples of strongly connected graphs with $|V| \in \{9, 10, 11\}$, for which we compute the true algebraic connectivity. The default validation set comprises 10'000 graphs with $|V| \in \{9, 10, 11\}$. We train using the loss function $\mathcal{L}_2$, and our results report the error $\mathcal{L}_1$:

$$\mathcal{L}_2 = \frac{1}{2|V|} \sum_i (\hat{\lambda}_{2,i} - \lambda_2)^2, \quad \mathcal{L}_1 = \frac{1}{2|V|} \sum_i |\hat{\lambda}_{2,i} - \lambda_2|.$$  

Figure 1 shows an example of a network topology and the connectivity values predicted through our model with a local readout. Figure 2 shows the average $\mathcal{L}_1$ error over validation sets, as training progresses, for three local and three global GNNs with varying messaging durations. As expected, global performs better than local, and higher $T$ perform better than lower $T$. Interestingly, increasing $T$ to 4 in the local model enables it to outperform $T = 2$ in the global model.

Figure 3 shows the ability of the models to generalize beyond the graph sizes they were trained on. As expected, the loss increases with the distance to known network sizes. For known graph size instances, the local model produces the somewhat counterintuitive result that its performance improves as graph sizes grow (the global model’s behavior is the inverse).

### 4 Conclusion

This short paper demonstrates the feasibility of learning distributed coordination mechanisms for robot team coordination. We trained Graph Neural Networks on random network topologies, to show that accurate distributed estimation of the network connectivity is achievable. Further work will consider team coordination mechanisms beyond distributed estimation, as shown in this work.

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1 http://github.com/Microsoft/gated-graph-neural-network-samples
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