Graph Neural Networks For Decentralized Controllers

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As the size of networks increasingly grows, centralized controllers face many limitations in terms of scalability and implementation. However, it is not straightforward to devise optimal controllers in a fully decentralized manner, where agents can only communicate with nearby agents and exchange information with them. Fortunately, Graph Neural Networks (GNNs) are naturally distributed architectures processing graph-structure data, perfectly rendering decentralized solutions. Motivated by this, the authors propose a framework employing GNNs to exploit the underlying graph topology and learn suitable controllers from data. More specifically, they adopt two different types of GNNs, i.e., graph convolutional neural networks (GCNNs) and graph recurrent neural networks (GRNNs), since both of them have the property of scalability and transferability. The former one implies both architectures maintain desirable performance in networks of an increasing number of agents. The latter one indicates that these learning models can be trained in one network and then transferred to another similar network. These appealing properties allow the authors to train the models via imitation learning methods, which require the availability of an optimal centralized controller during the offline training period but not during testing. Finally, this paper then explores the problem of flocking to illustrate the prominent effectiveness of GCNNs and GRNNs in learning decentralized controllers.