

Summary of: Learning Decentralized Controllers for Robotic Swarms with Graph Neural Networks

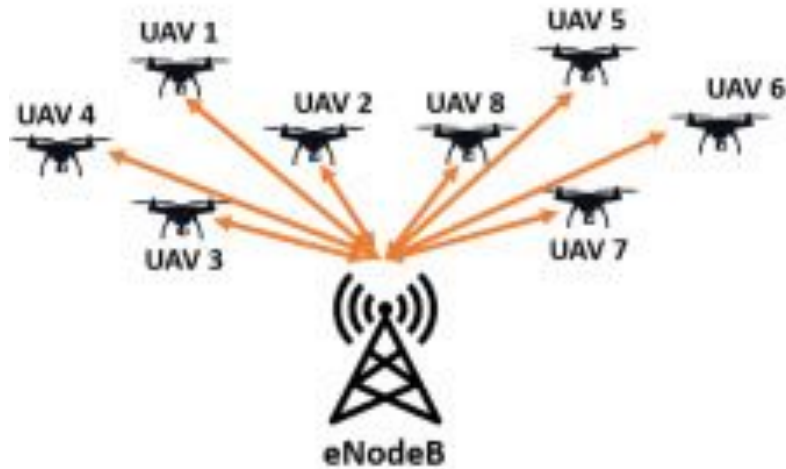
Written by: Ekaterina Tolstaya, Fernando Gama, James Paulos, George Pappas, Vijay Kumar, and Alejandro Ribeiro

Presented by: Austin Stone

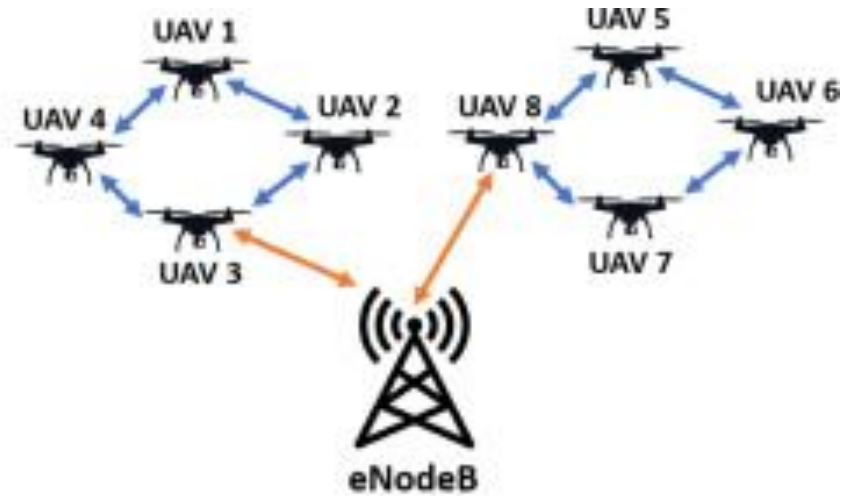
Outline

- Motivation
- Background
- Model
- Theoretical Results
- Simulation Results
- Summary
- Future Work

Motivation



(a) Centralized Model



(b) Decentralized Model

Relevant Background Literature

Referenced Papers:

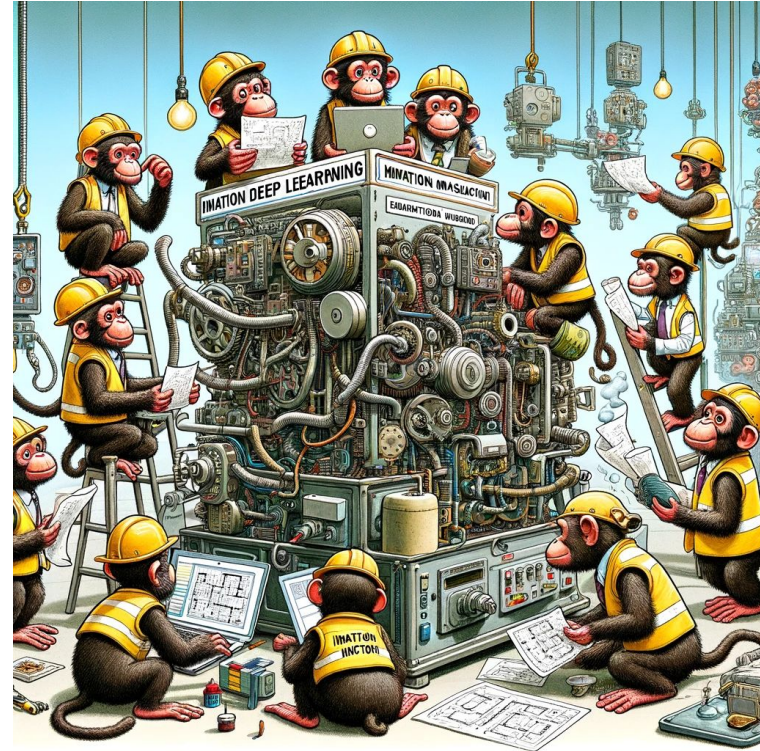
- **Imitation Control** – J. Paulos, S. W. Chen, D. Shishika, and K. Vijay. Decentralization of multiagent policies by learning what to communicate. In 2019 IEEE International Conference on Robotics and Automation (ICRA), Montreal, May 2019.
- **Aggregation NN** – F. Gama, A. G. Marques, G. Leus, and A. Ribeiro. Convolutional neural network architectures for signals supported on graphs. IEEE Trans. Signal Process., 67(4):1034–1049, Feb. 2019.
- **Local Controller/Global Controller** – H. G. Tanner, A. Jadbabaie, and G. J. Pappas. Stable flocking of mobile agents part ii: dynamic topology. In Decision and Control, 2003. Proceedings. 42nd IEEE Conference on, volume 2, pages 2016–2021. IEEE, 2003.

Main Contribution:

- Train Graph NN to do flocking

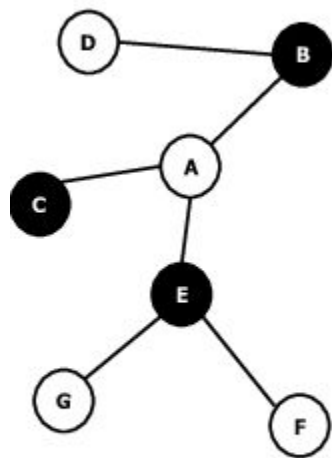
Imitation Control

Monkey See, Monkey Do

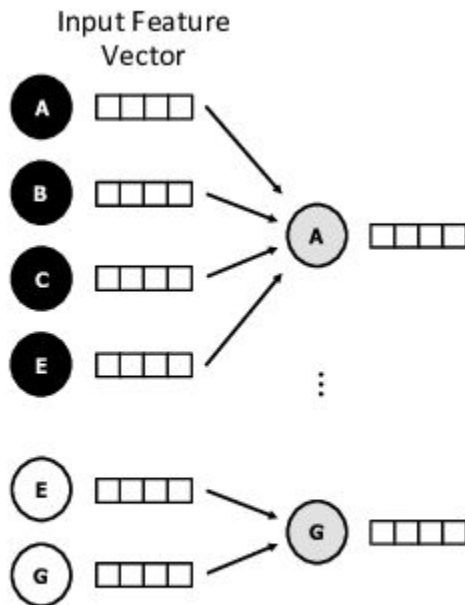


Presenter generated with Dalle3

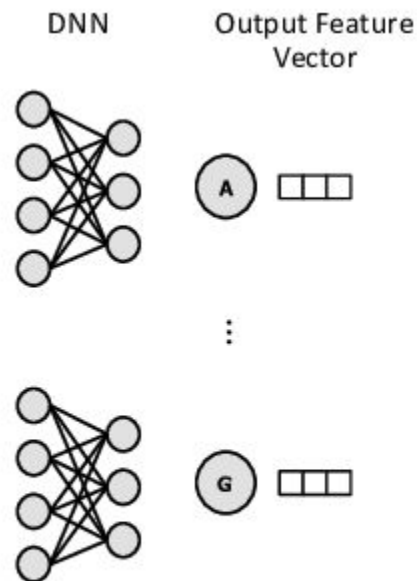
Aggregation Graph Neural Networks



(a) Input Graph



(b) Aggregation



(c) Combination

Global Controller

$$U(r_i, r_j) = \begin{cases} \frac{1}{\|r_{ij}\|^2} - \log(\|r_{ij}\|^2) & \text{if } \|r_{ij}\| > \rho \\ \frac{1}{\rho^2} - \log(\rho^2) & \text{otherwise} \end{cases}$$

$$\nabla_{r_i} U(r_i, r_j) = \begin{cases} -\frac{2r_{ij}}{\|r_{ij}\|^4} + \frac{2r_{ij}}{\|r_{ij}\|^2} & \text{if } \|r_{ij}\| > \rho \\ 0 & \text{otherwise} \end{cases}$$

$$u_i^* = -\sum_{j=1}^N (v_i - v_j) - \sum_{j=1}^N \nabla_{r_i} U(r_i, r_j).$$

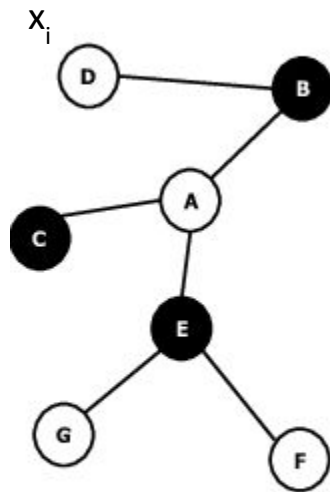
Local Controller

$$u_i^\dagger = - \sum_{j \in \mathcal{N}_i} (v_i - v_j) - \sum_{j \in \mathcal{N}_i} \nabla_{r_i} U(r_i, r_j).$$

A still from the movie 'Back to the Future' showing Dr. Emmet Brown (played by Christopher Lloyd) and Marty McFly (played by Michael J. Fox). Dr. Brown is on the left, wearing his signature wild white hair and a white lab coat, holding the flux capacitor with a look of intense concentration. Marty is on the right, wearing a red puffy jacket and a leather vest, looking on with a concerned expression. The scene is set at night with a dark background and some blurred lights in the distance.

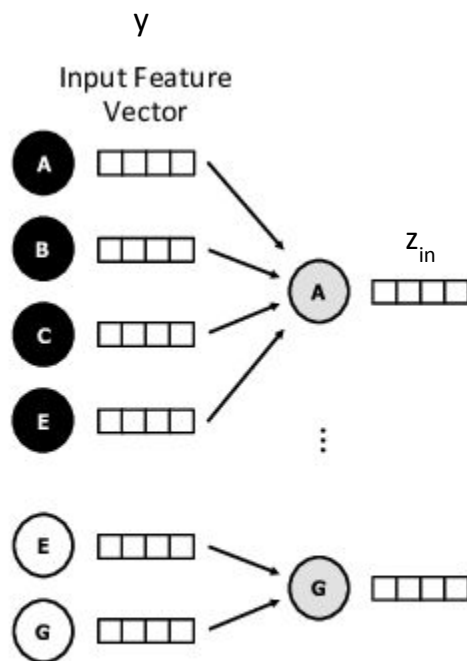
Back to the Future!

Summary

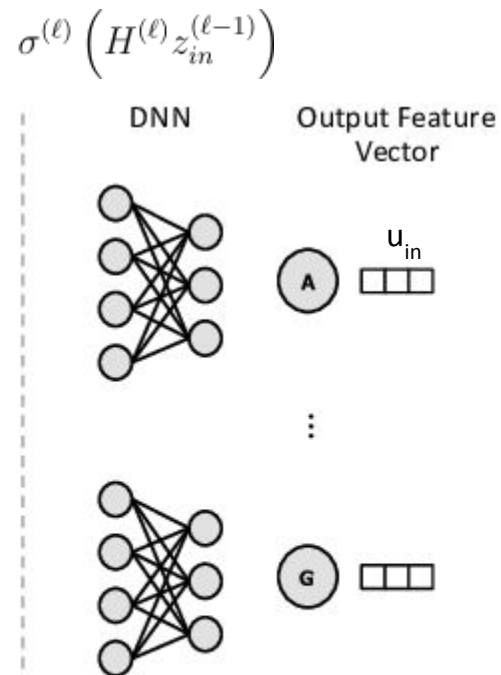


(a) Input Graph

S_n



(b) Aggregation

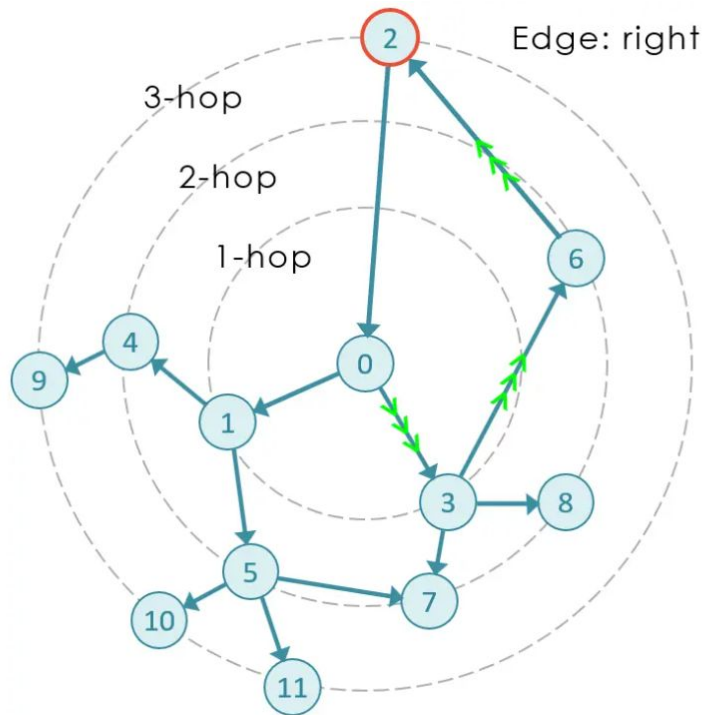


(c) Combination

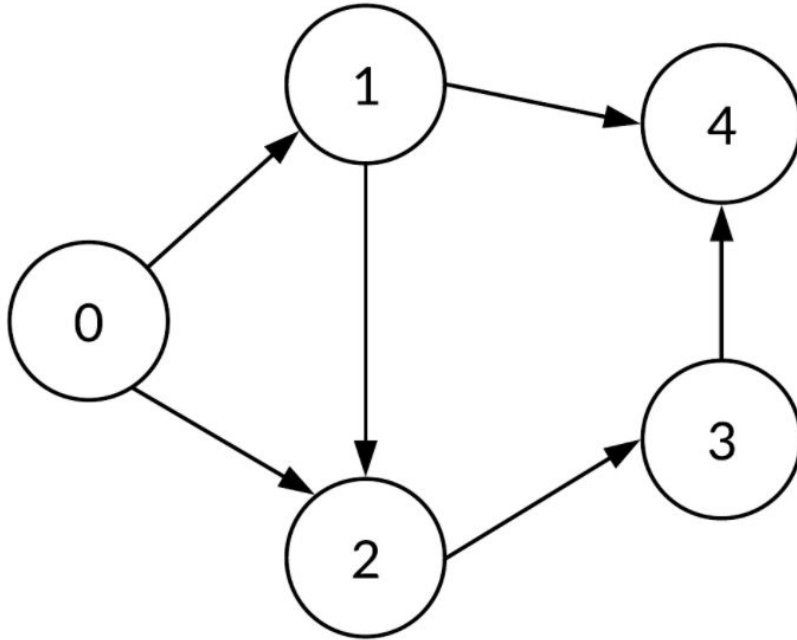
k-hops

$$\mathcal{N}_{in}^k = \{j' \in \mathcal{N}_{j(n-1)}^{k-1} \mid j' \in \mathcal{N}_{in}\}$$

$$\mathcal{H}_{in} = \bigcup_{k=0}^{K-1} \{x_{j(n-k)} : j \in \mathcal{N}_{in}^k\}$$



Graph Shift Operator



~~Adjacency Matrix~~ Graph Shift Operator $[S_n]$

	0	1	2	3	4
0	0	1	1	0	0
1	0	0	1	0	1
2	0	0	0	1	0
3	0	0	0	0	1
4	0	0	0	0	0

Feature Matrix

$$y_{kn} = S_n y_{(k-1)(n-1)},$$

$$[y_{0n}]_i = [x_n]_i = x_{in}^T$$

$$z_{in} = [[y_{0n}]_i; [y_{1n}]_i; \dots; [y_{(K-1)n}]_i]$$

Feature Vector

$$[x_n]_i = \left[\sum_{j \in \mathcal{N}_i} (v_{i,n} - v_{j,n}), \sum_{j \in \mathcal{N}_i} \frac{r_{ij,n}}{\|r_{ij,n}\|^4}, \sum_{j \in \mathcal{N}_i} \frac{r_{ij,n}}{\|r_{ij,n}\|^2} \right]$$

Final Control / Loss Function

$$z_{in}^{(\ell)} = \sigma^{(\ell)} \left(H^{(\ell)} z_{in}^{(\ell-1)} \right)$$

$$H^* = \operatorname{argmin}_H \sum_{(x_n, \pi^*(x_n)) \in \mathcal{T}} \mathcal{L}(u_n, u_n^*)$$

DAgger (Dataset Aggregation)

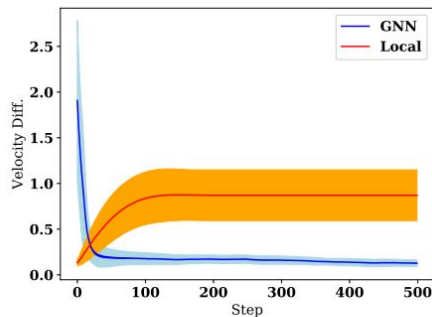
For each iteration:

- Generate a trajectory where, for each timestep, the expert policy is selected with probability β and the learner's policy is selected with probability $1 - \beta$.
- Train using the generated trajectory.
- Decay β by a factor of γ until it reaches β_{\min} .

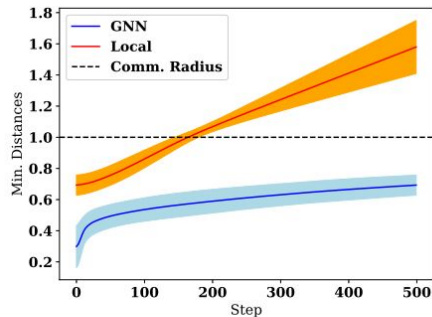
Theoretical Results

- Leans on the previous theoretical results demonstrating global controller convergence.
- Doesn't show much theory as to why training works.

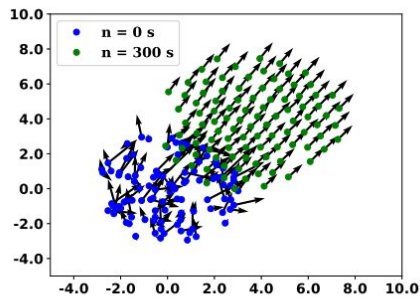
Simulation Results



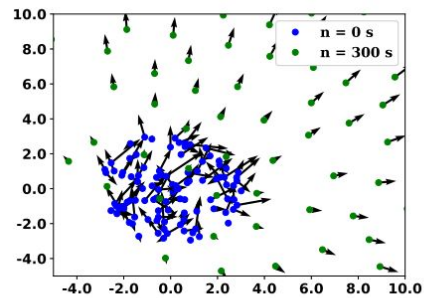
(a) Average difference in velocities



(b) Average minimum distance to a neighbor

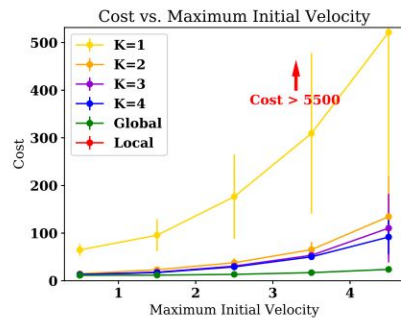


(c) Flock positions using the GNN

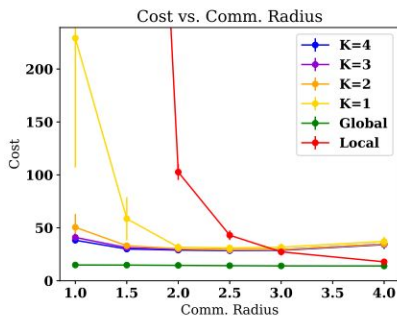


(d) Flock positions using the local controller

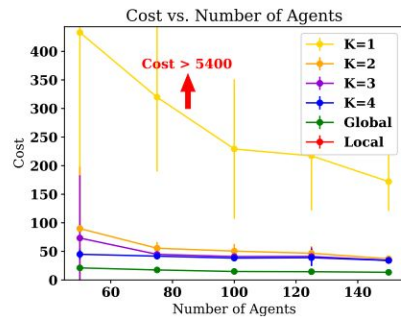
Simulation Results (Continued)



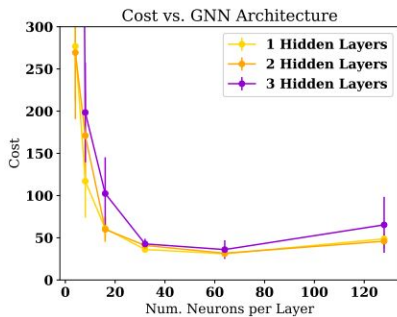
(a)



(b)



(c)



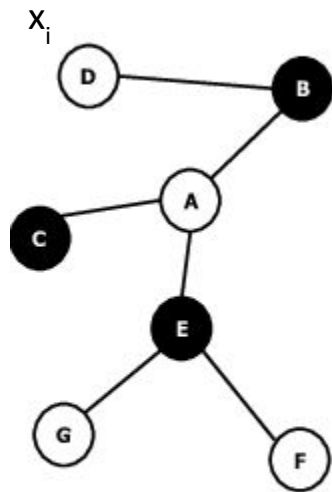
(d)

My Results/Their Results Again

Their code can be found at:

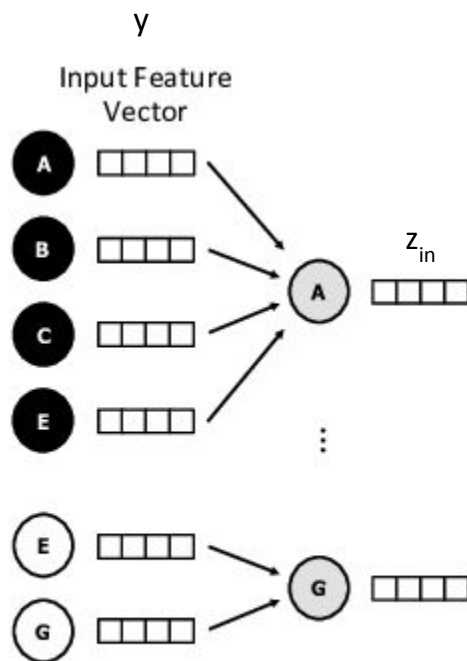
https://github.com/katetolstaya/multiagent_gnn_policies/tree/master

Summary

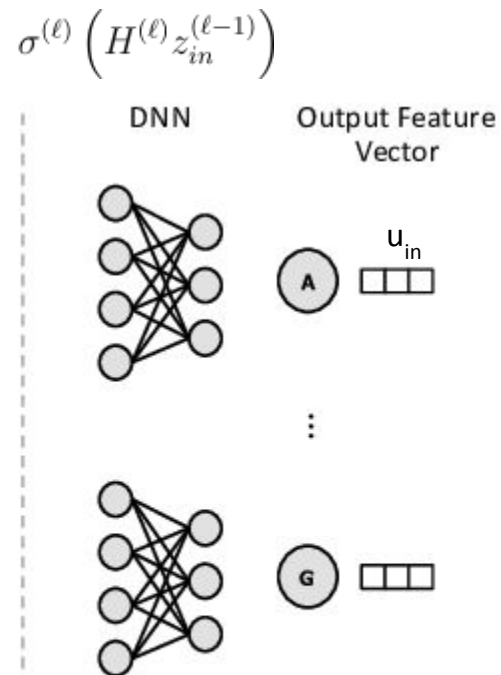


(a) Input Graph

S_n



(b) Aggregation



(c) Combination

Future Work

- Hardware verification
- Many other imitation learning tasks
- Different Graph NN Architectures