UCI Samueli School of Engineering

Task-Scheduling for Multi-Robot Systems with Heterogeneous Graph Neural Networks

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Course: EECS 298 – Network Science

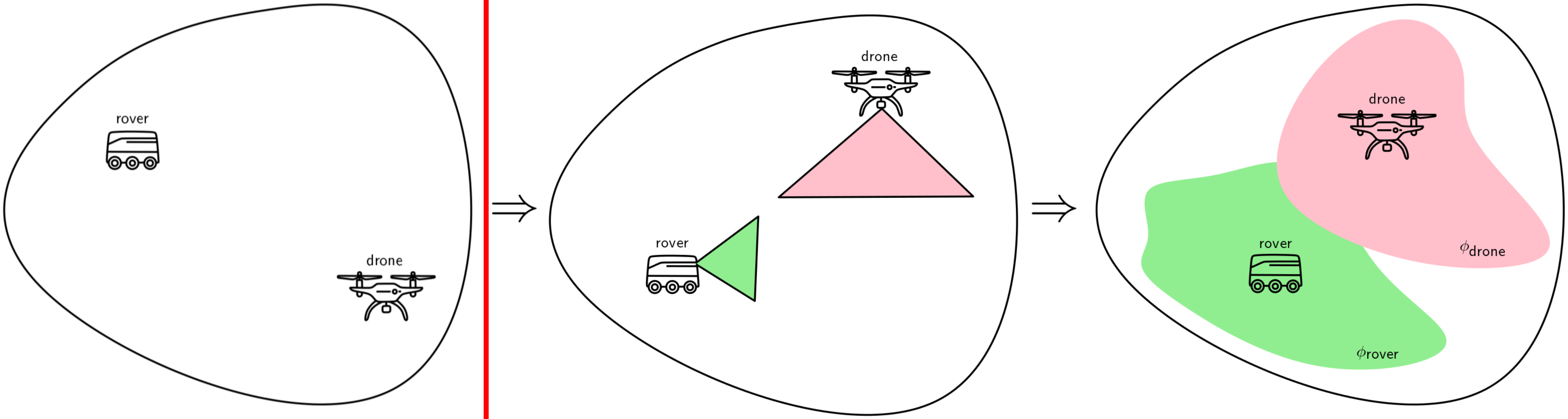
UCI Samueli School of Engineering

Talk Outline

- Project Proposal Overview
- Literature Review
- Background on Graph Attention Networks
- ScheduleNet
- Results
- Future Work

Project Proposal Overview

Robots with **different types** of **sensing** modalities **collaborate** to **“paint a better picture of the world”**

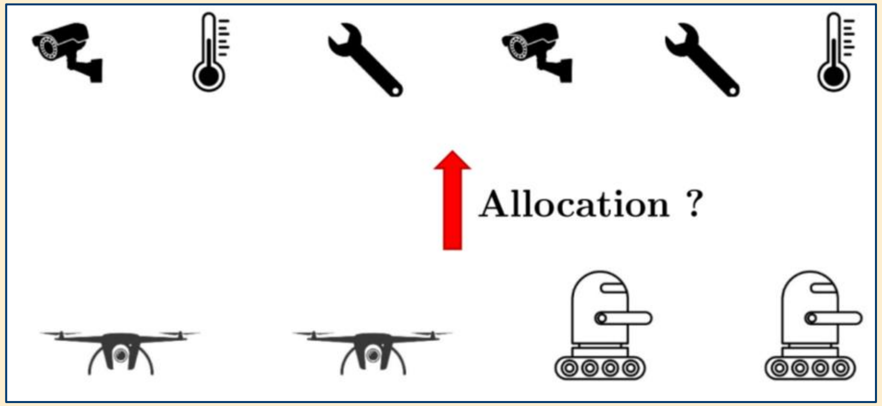


Task-Scheduling

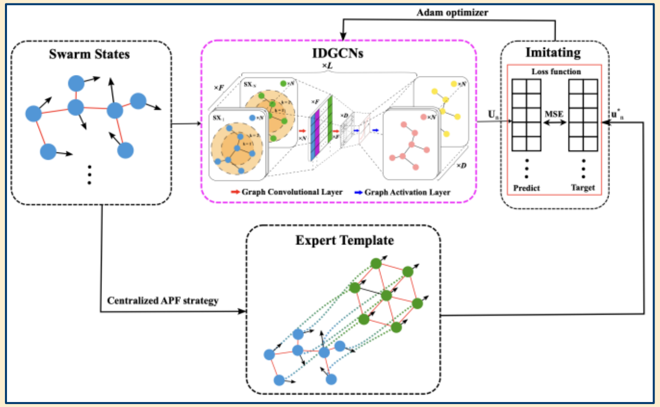
Information Gathering
&
Sensor Fusion

Coverage Control

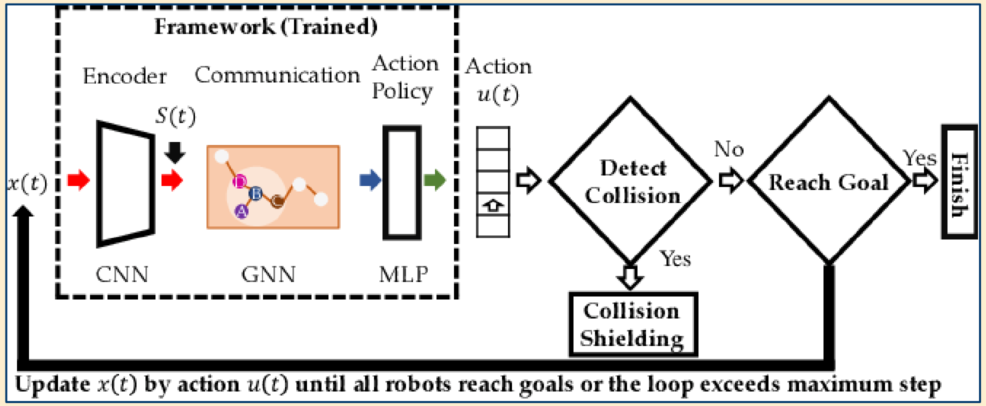
Background on Resource Allocation and Graph Neural Networks (GNNs)



Task Allocation in Heterogeneous Robot Teams [1]



GNNs in Homogeneous Swam Robotics [2]



GNN for Multi-Robot Communication [3]

[1] H. Chakraa, F. Guerin, E. Leclercq, and D. Lefebvre, "Optimization techniques for Multi-Robot Task Allocation problems: Review on the state-of-the-art," in *Robotics and Autonomous Systems*, vol. 168, p. 104492, Oct. 2023.
[2] C. Guo, P. Zhu, Z. Zhou, L. Lang, Z. Zeng, and H. Lu, "Imitation Learning with Graph Neural Networks for Improving Swarm Robustness under Restricted Communications," in *Applied Sciences*, vol. 11, no. 19, p. 9055, Sept. 2021.
[3] Q. Li, F. Gamma, A. Ribeiro, and A. Prorok, "Graph neural networks for decentralized multi-robot path planning," in *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2020, pp. 11785-11792.

Graph Attention Networks

The input and output set of node features is defined as

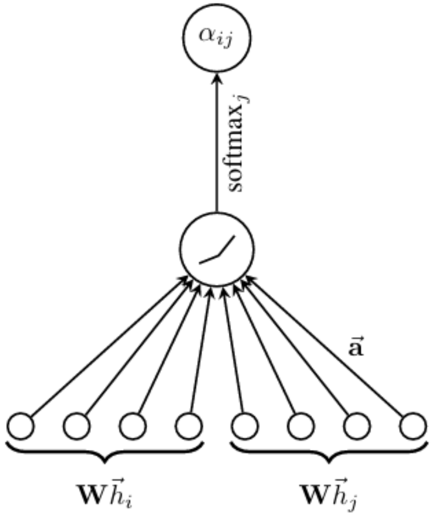
$$\mathbf{h} = \{\vec{h}_1, \ldots, \vec{h}_N\}, \quad \vec{h}_i \in \mathbb{R}^F \qquad \text{(Input)}$$

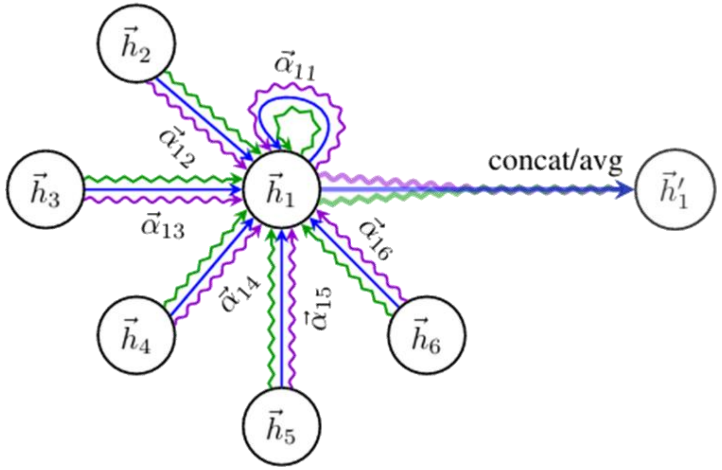
$$\mathbf{h}' = \{\vec{h}'_1, \ldots, \vec{h}'_N\}, \quad \vec{h}'_i \in \mathbb{R}^{F'} \qquad \text{(Output)}$$

where *N* is the number of nodes, and *F* and *F’* (of potentially different cardinality than *F*) are the number of features in each node.

$\mathbf{W} \in \mathbb{R}^{F' \times F}$ is the weight matrix allowing us to focus attention on specific features

$a : \mathbb{R}^{F' \times F} \rightarrow \mathbb{R}$ is the attention mechanism that uses nonlinear activation function(e.g: LeakyReLU) to output **attention scores**

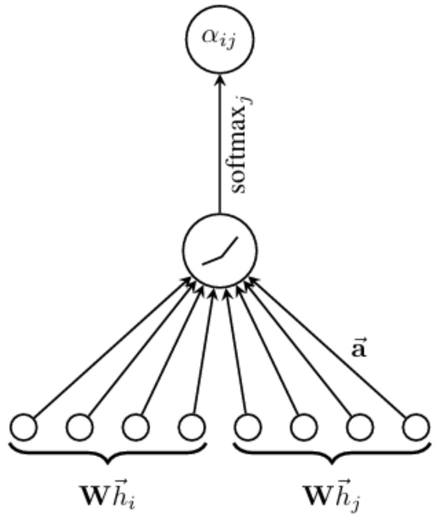




P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Liò, and Y. Bengio, “Graph attention networks,” in *Proceedings of International Conference on Learning Representations*, 2018.

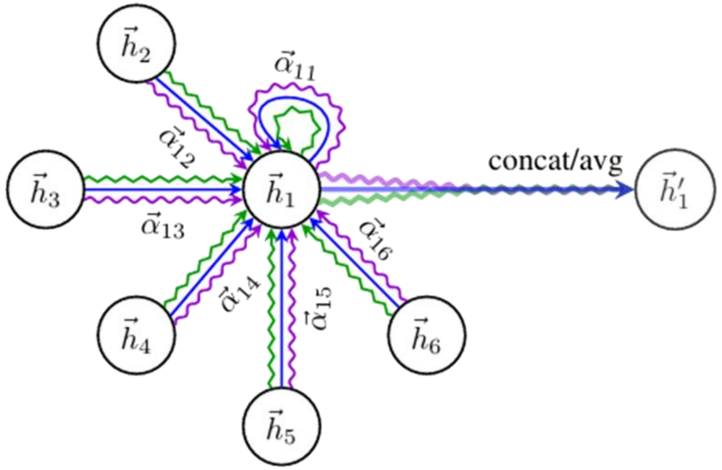
Graph Attention Networks

Attention coefficients, e_{ij}, indicate the importance of node j's features to node i:



$$e_{ij} = a(\mathbf{W}\vec{h}_i, \mathbf{W}\vec{h}_j)$$

Graph structure information is injected via masked attention (α_{ij})
– i.e., compute e_{ij} for node $j \in \mathcal{N}_i$ (neighborhood set of node *i*, which includes node *i)*



$$\alpha_{ij} = \text{softmax}(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik})}$$

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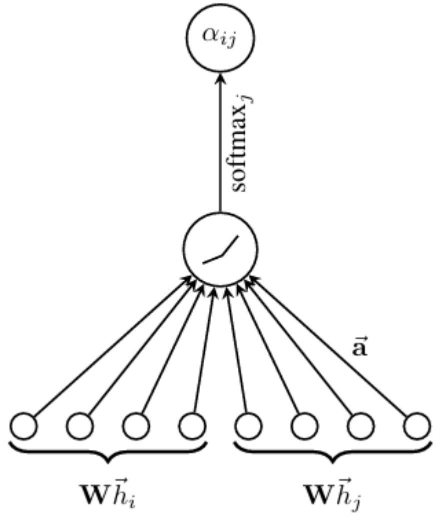
Multi-Head Graph Attention Networks

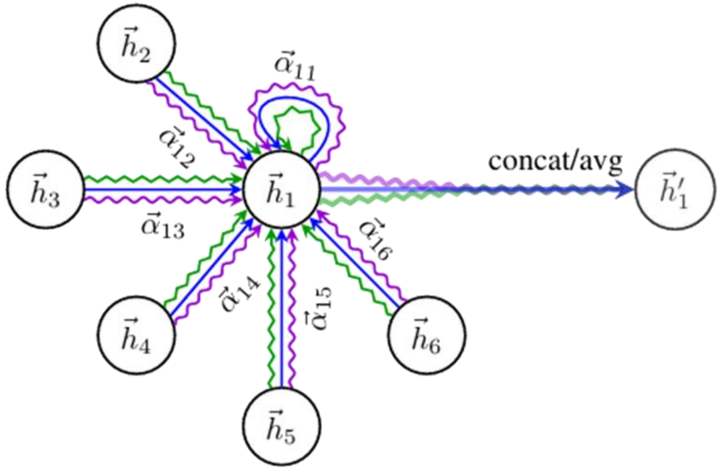
Multi-head attention in intermediate layers applies a nonlinearity activation function and then **concatenates**.

$$\vec{h}'_i = \Big\Vert_{k=1}^{K} \sigma\left(\sum_{j\in\mathcal{N}_i} \alpha_{ij}^{k}\mathbf{W}^{k}\vec{h}_j\right)$$

Multi-head attention at the final layer **averages** the values and then applies nonlinearity activation function.

$$\vec{h}'_i = \sigma\left(\frac{1}{K}\sum_{k=1}^{K}\sum_{j\in\mathcal{N}_i} \alpha_{ij}^{k}\mathbf{W}^{k}\vec{h}_j\right)$$





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ScheduleNet

$$\min(z) \tag{1}$$

$$\sum_{r \in \boldsymbol{r}} A_{r,i} = 1, \forall \tau_i \in \boldsymbol{\tau} \tag{2}$$

$$f_i - s_i = \sum_{r \in \boldsymbol{r}} dur_{i,r} A_{r,i}, \forall \tau_i \in \boldsymbol{\tau} \tag{3}$$

$$f_i - s_0 \leq d_i, \forall d_i \in \boldsymbol{d} \tag{4}$$

$$s_i - f_j \geq w_{i,j}, \forall w_{i,j} \in \boldsymbol{w} \tag{5}$$

$$(s_j - f_i) A_{r,i} A_{r,j} X_{i,j} \geq 0, \forall \tau_i, \tau_j \in \boldsymbol{\tau}, \forall r \in \boldsymbol{r} \tag{6}$$

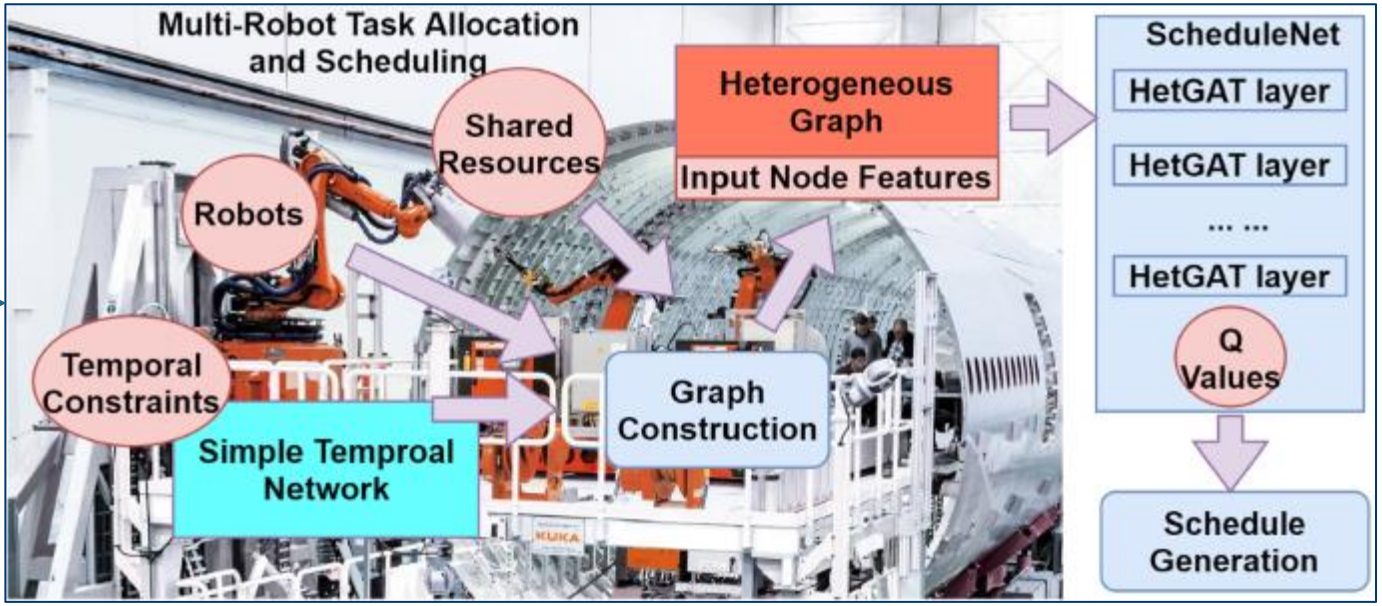
$$(s_i - f_j) A_{r,i} A_{r,j} (1 - X_{i,j}) \geq 0, \forall \tau_i, \tau_j \in \boldsymbol{\tau}, \forall r \in \boldsymbol{r} \tag{7}$$

$$(s_j - f_i) X_{i,j} \geq 0, \forall (\tau_i, \tau_j) \in \boldsymbol{L_{proximity}} \tag{8}$$

$$(s_i - f_j)(1 - X_{i,j}) \geq 0, \forall (\tau_i, \tau_j) \in \boldsymbol{L_{proximity}} \tag{9}$$

Mixed Integer Linear Program for task-scheduling with temporospatial constraints [4]

NP-Hard!



Overview of the ScheduleNet Framework [5]

[4] Z. Wang, C. Liu, and M. Gombolay, “Heterogeneous graph attention networks for scalable multi-robot scheduling with temporospatial constraints,” in *Autonomous Robots*, vol. 46, pp. 249-268, Aug. 2021.

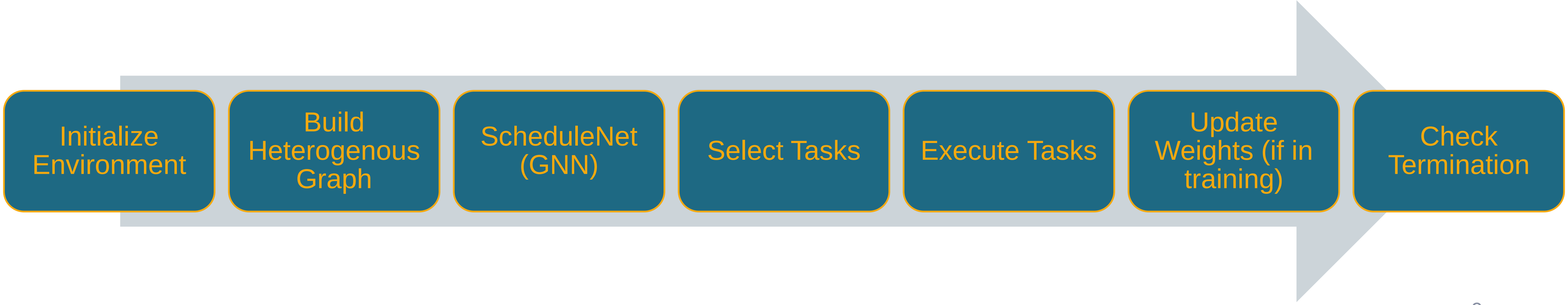
ScheduleNet

Heterogenous Graph

- *Nodes:* tasks, robots
- *Edges:* communication links
- *Node features:* durations, positions, feasibility, etc.

GNN Architecture

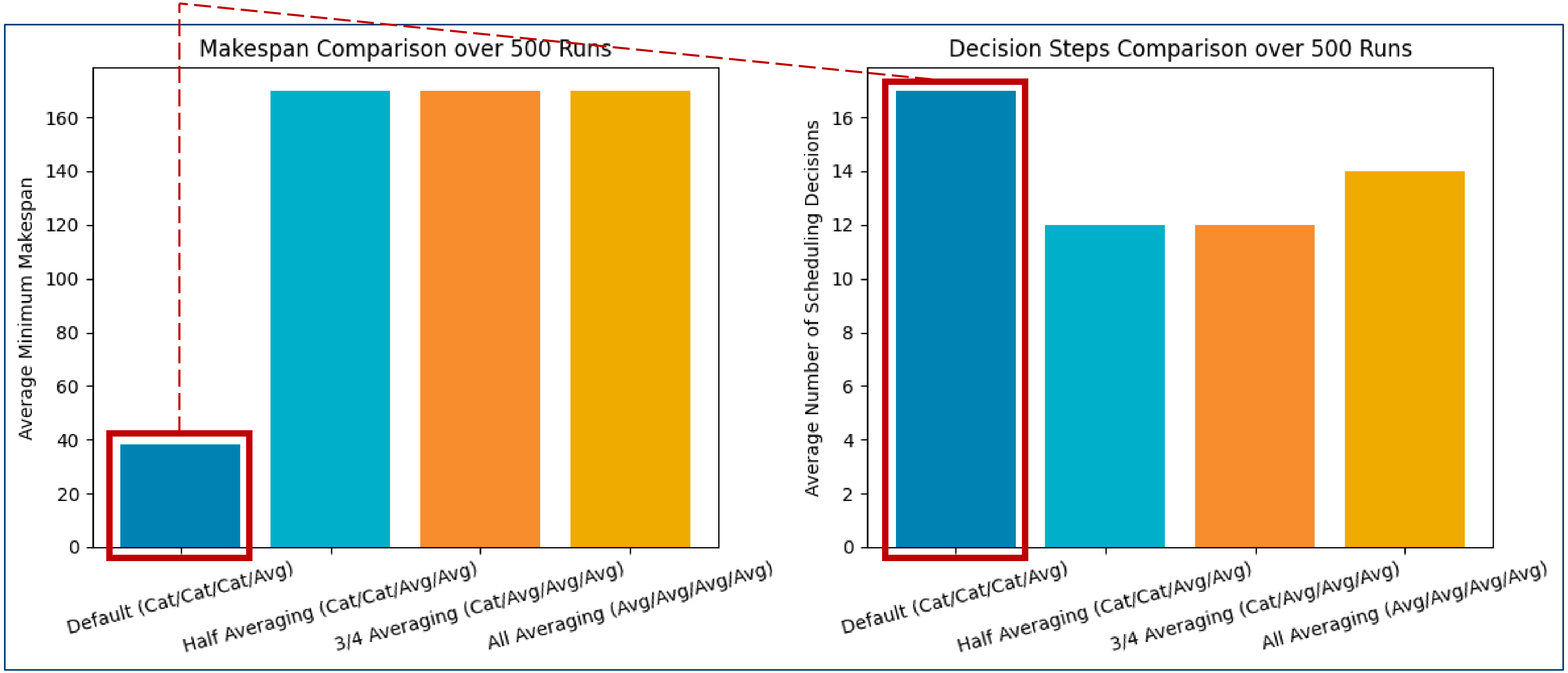
- *HeteroGATLayer:* handles multi-edge-type attention.
- *MultiHeteroGATLayer:* uses multi-head attention and merges via 'cat' or 'avg'.
- *ScheduleNet4Layer:* stacks 4 multi-head GAT layers to produce final node embeddings.



[4] Z. Wang, C. Liu, and M. Gombolay, “Heterogeneous graph attention networks for scalable multi-robot scheduling with temporospatial constraints,” in *Autonomous Robots*, vol. 46, pp. 249-268, Aug. 2021.

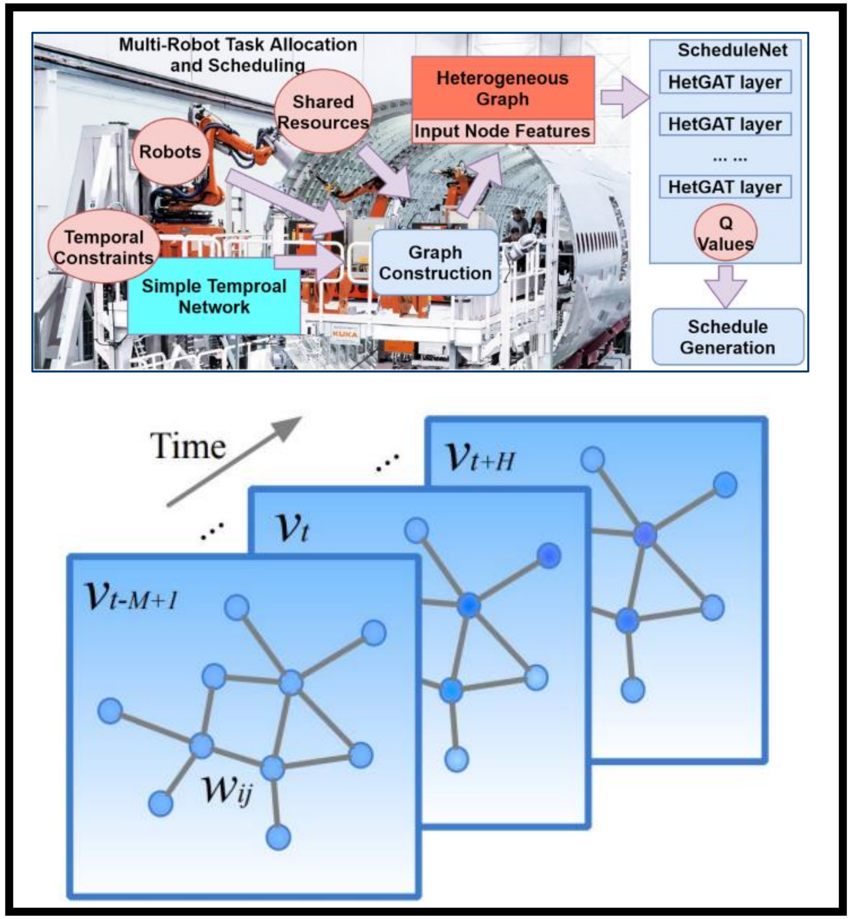
Results

ScheduleNet Aggregation

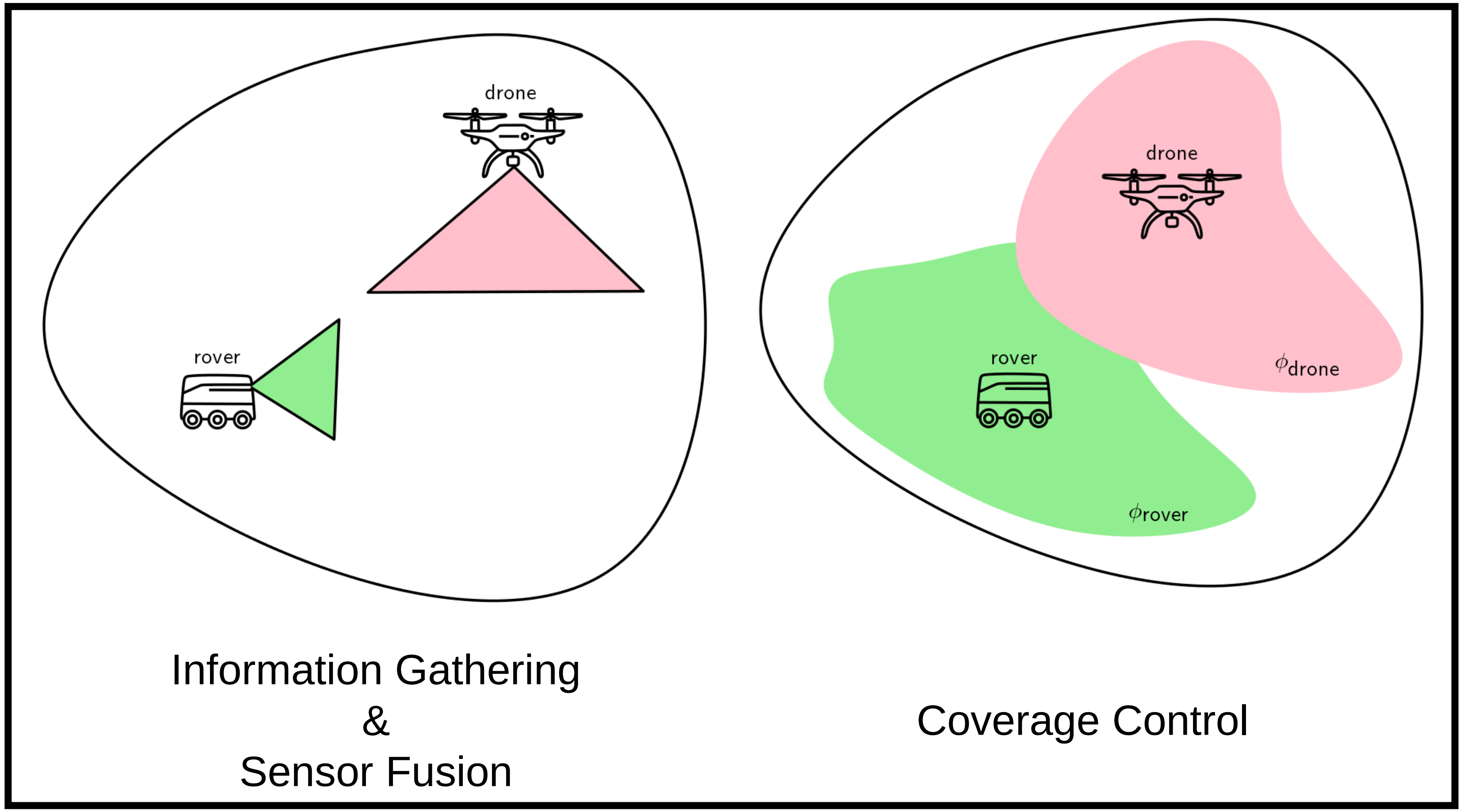


Future Work

Extend ScheduleNet to consider Dynamic Graphs



Collaborative perception with GNNs



Thank You for Listening!