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Carnegie Mellon University

# GiPH: Generalizable Placement Learning for Adaptive Heterogeneous Computing

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[3]Google

# Overview

- **Placement in Heterogeneous Computing**
  - Motivation
  - Problem Formulation
- **Related Work**
- **GiPH**
- **Evaluation**
- **Conclusion**

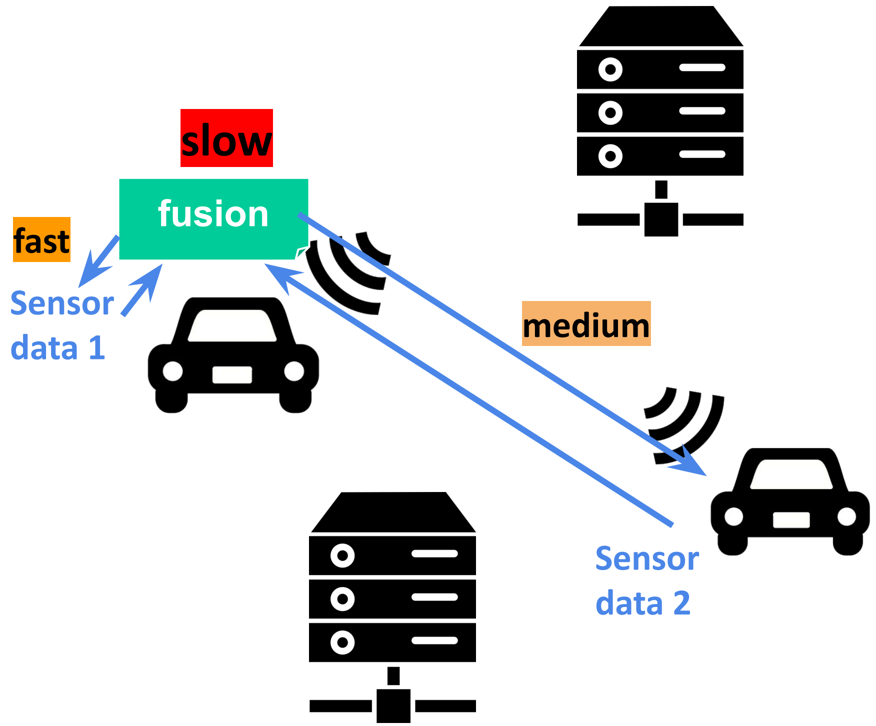
# Motivation

- **Highly distributed, hundreds of nodes: *LATENCY***
  - Time-sensitive data processing
  - Precise timing requirements
  - Eg., light-free traffic control

Source: 'Rush Hour' by Black Sheep Films

# Placement is the KEY

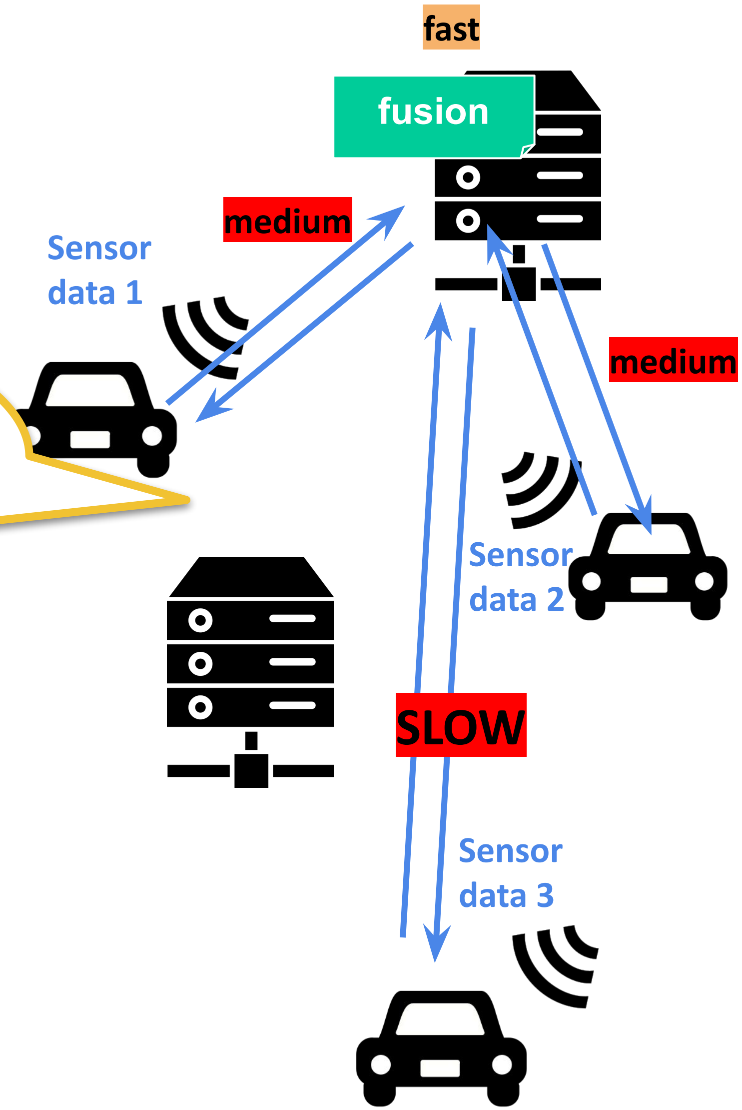
## Example: sensor fusion



# Placement is the KEY

## Example: sensor fusion

Communication and computation time tradeoff (comm/comp capabilities)



# Placement is the KEY

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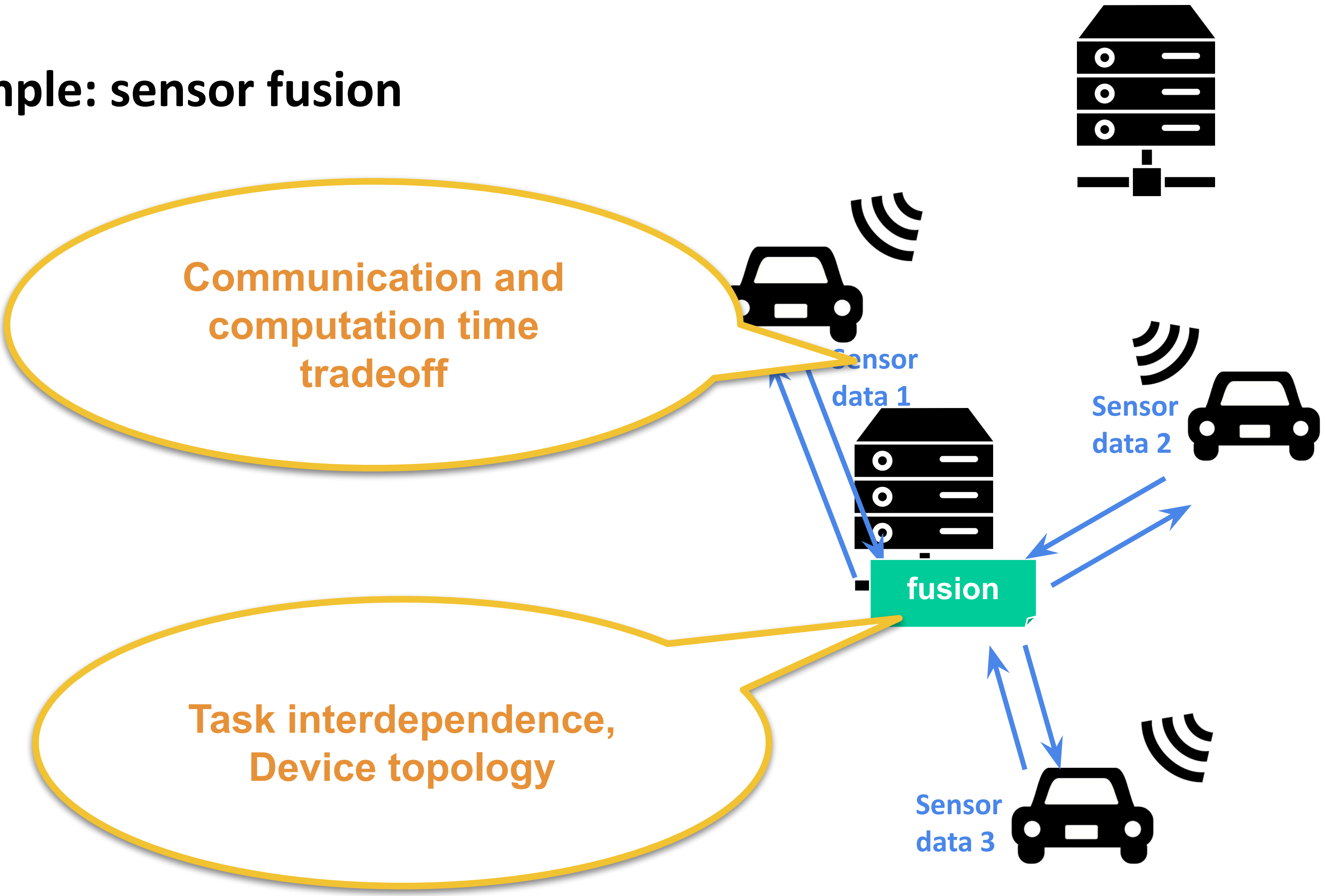
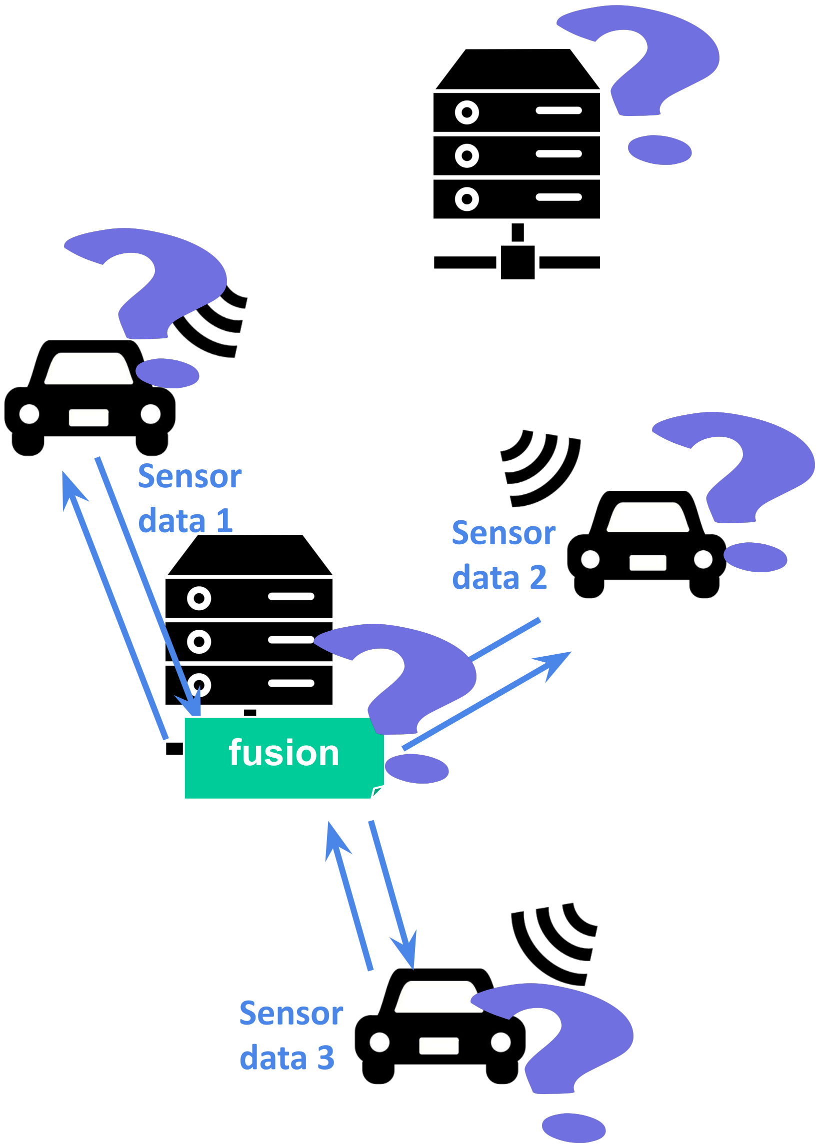


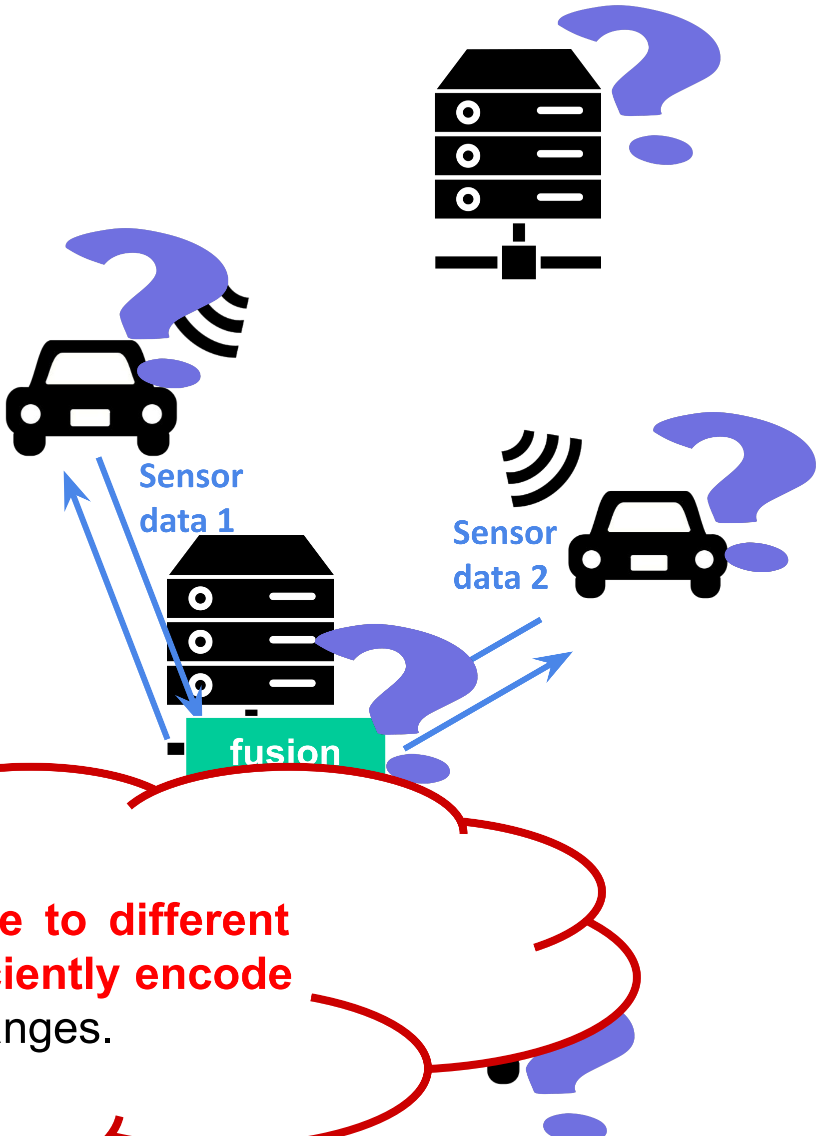
# Placement is the KEY

**Challenges:**

- Devices are ***heterogeneous***
  - Different types:
    - CPUs/GPUs
    - PCs/Servers/UEs
  - Various compute/communication capabilities - *tradeoff*
  - Functionalities
- Devices can be ***volatile***
  - Some device becomes unavailable
  - New device enters the system



# Placement is the KEY

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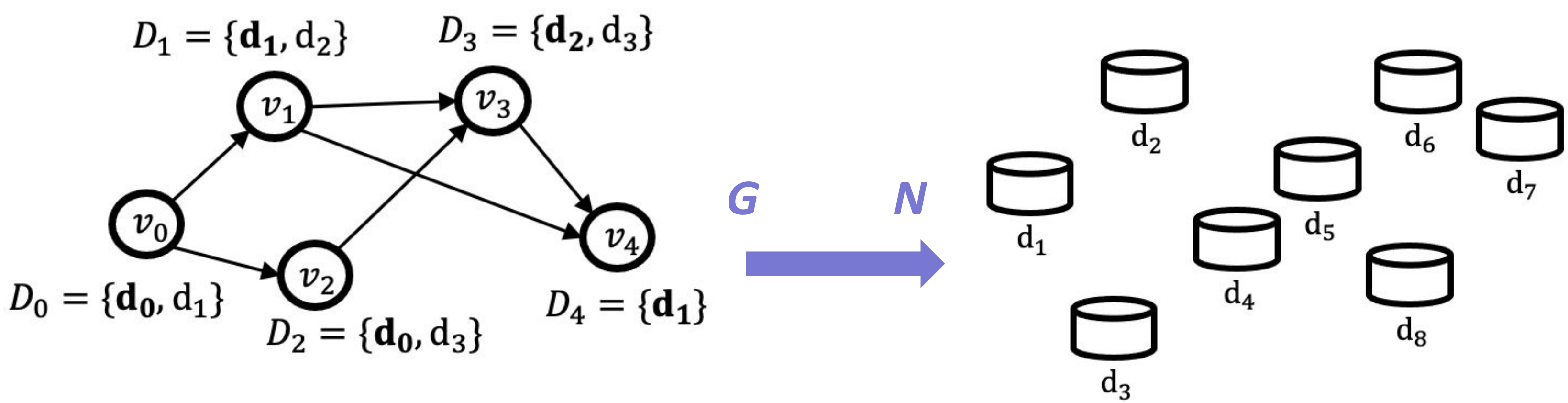
- Devices can be ***volatile***
  - Some device becomes unavailable
  - New

Require a solution that can **scale to different number of devices** and can **efficiently encode information** as the device set changes.

# Placement Problem




**A compute application *G* (DAG)**

The set of tasks *V*

with placement constraints $D_i \subseteq D$

**A target computing network *N***

The set of devices *D*

**Placement** $\mathcal{M}^{G \to N} : V \to D$

**Objective** $\min \rho(\mathcal{M}|G, N) \quad \text{s.t } \mathcal{M}(v_i) \in D_i$

# Placement: Makespan Minimization

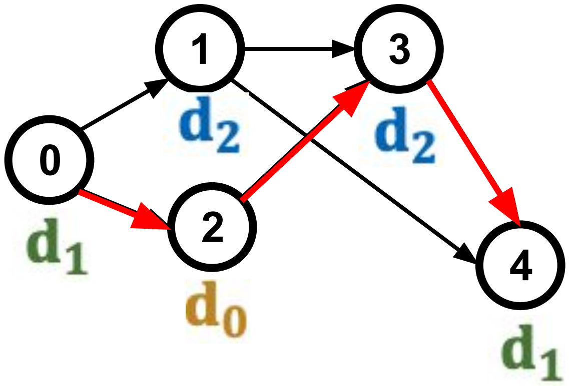
For time-sensitive applications, it is important to minimize the ***completion time***, i.e., makespan

- The time duration from the start of the first task's execution to the end of the last task's execution

$$\min_{\mathcal{M}} \rho(\mathcal{M}|G,N) = \min_{\mathcal{M}} \max_{p \in P(G)} \left( \sum_{i \in p} c_i + \sum_{(i,j) \in p} c_{ij} \right)$$

- The total cost along the critical path
- Depends on the placement of all tasks
- NP-hard

**Hard to place the whole graph all at once!**

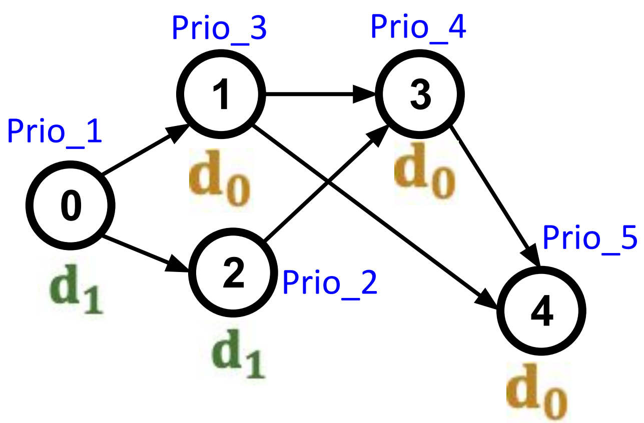


# Related Work

- Scheduling Heuristics in Heterogeneous Computing
- RL-based Device Placement for Neural Network Training

# Related Work: Scheduling Heuristics

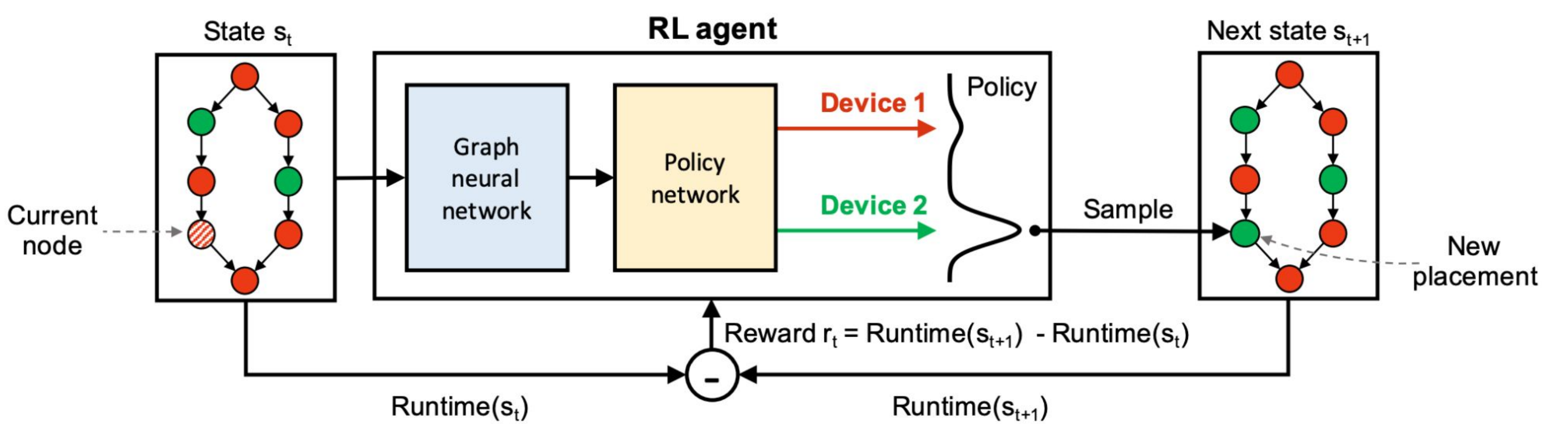
- **Rely on simple strategies and hand-crafted features**
- **E.g., Heterogeneous Earliest Finish Time (*HEFT*)[1]**
  - Give each task a priority that maintains the topological ordering of the tasks
  - Starting with the highest priority, place each task to a device that will result in the *earliest finish time* (EFT) of that task




[1] H. Topcuoglu, S. Hariri and Min-You Wu, "Performance-effective and low-complexity task scheduling for heterogeneous computing," in *IEEE Transactions on Parallel and Distributed Systems*, vol. 13, no. 3, pp. 260-274, March 2002, doi: 10.1109/71.993206.

# Related Work: RL-based Device Placement

- **Predict a placement for each task**
- **Hierarchical model for device placement (*HDP*)[2]**
  - An RL policy is trained for each graph
  - An RNN-based placer: encoder/decoder pair to predict one device for each node in the order of the inputs
  - *Does not generalize to new neural networks/device clusters*
- ***Placeto*[3]**
  - A GNN is used to embed graph-level features
  - *Does not generalize to new device clusters*




[2] Mirhoseini, Azalia et al. "A Hierarchical Model for Device Placement." *International Conference on Learning Representations* (2018).
[3] Ravichandra Addanki, Shaileshh Bojja Venkatakrishnan, Shreyan Gupta, Hongzi Mao, and Mohammad Alizadeh. 2019. Placeto: learning generalizable device placement algorithms for distributed machine learning. Proceedings of the 33rd International Conference on Neural Information Processing Systems. Curran Associates Inc., Red Hook, NY, USA, Article 358, 3981–3991.

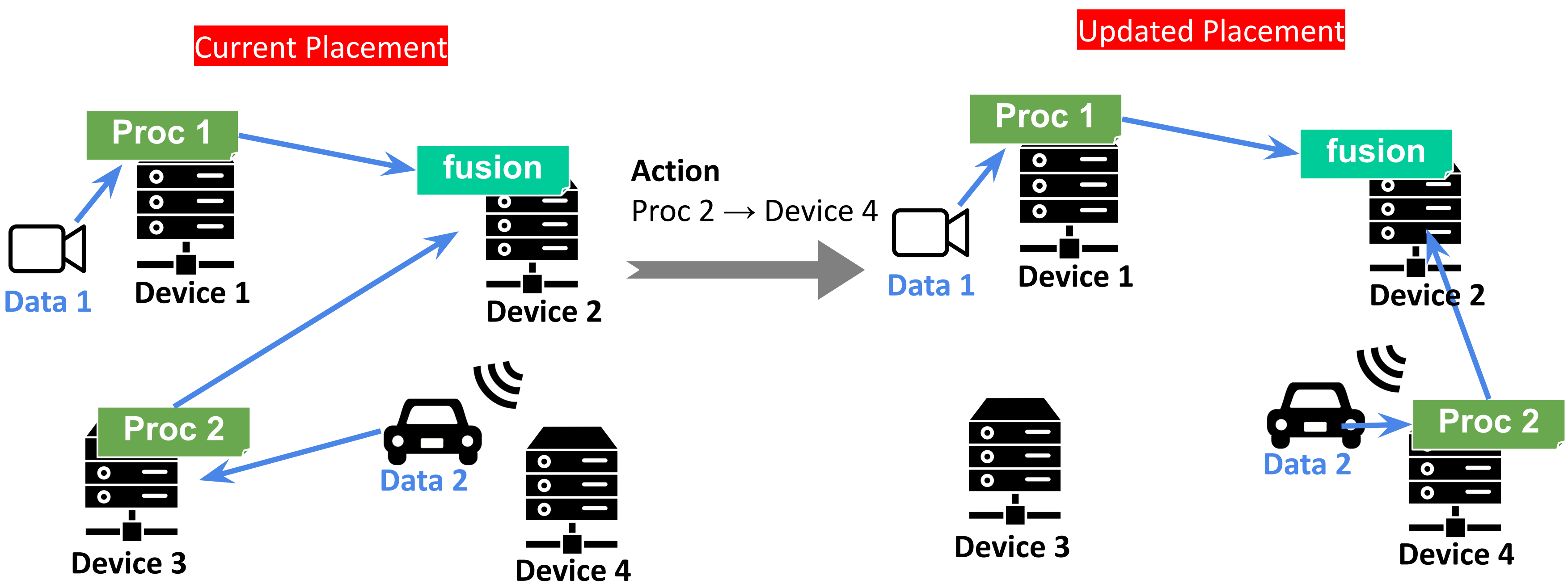
# GiPH

- Fully generalizable placement learning
- Adaptive to network changes

# MDP Formalism

We formulate the placement problem as a ***search problem***, where ***incremental changes*** are made to the current placement.

- Current placement→ **take an action (update the current placement) → transition to a new state → reward (improvement)**

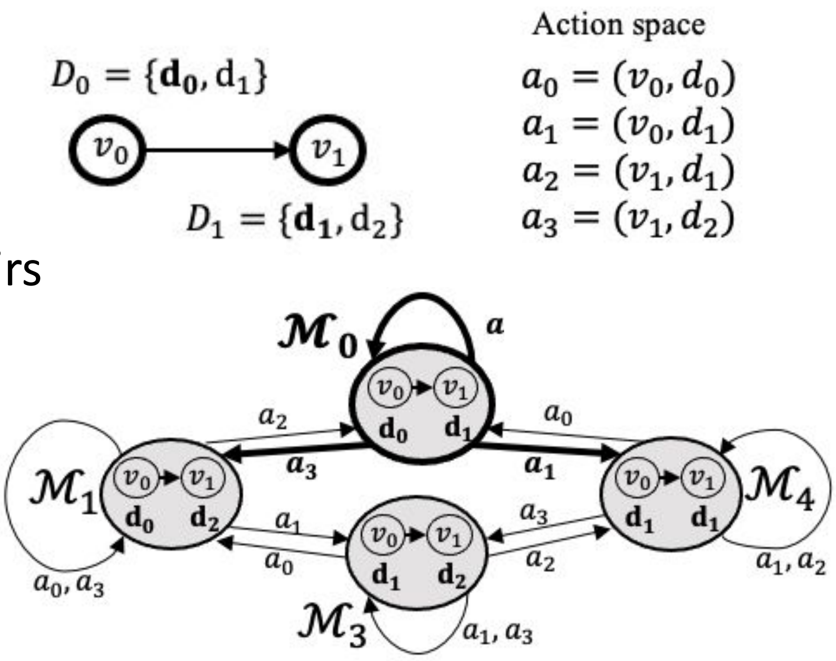


# MDP Formalism

We formulate the placement problem as a ***search problem***, where ***incremental changes*** are made to the current placement.

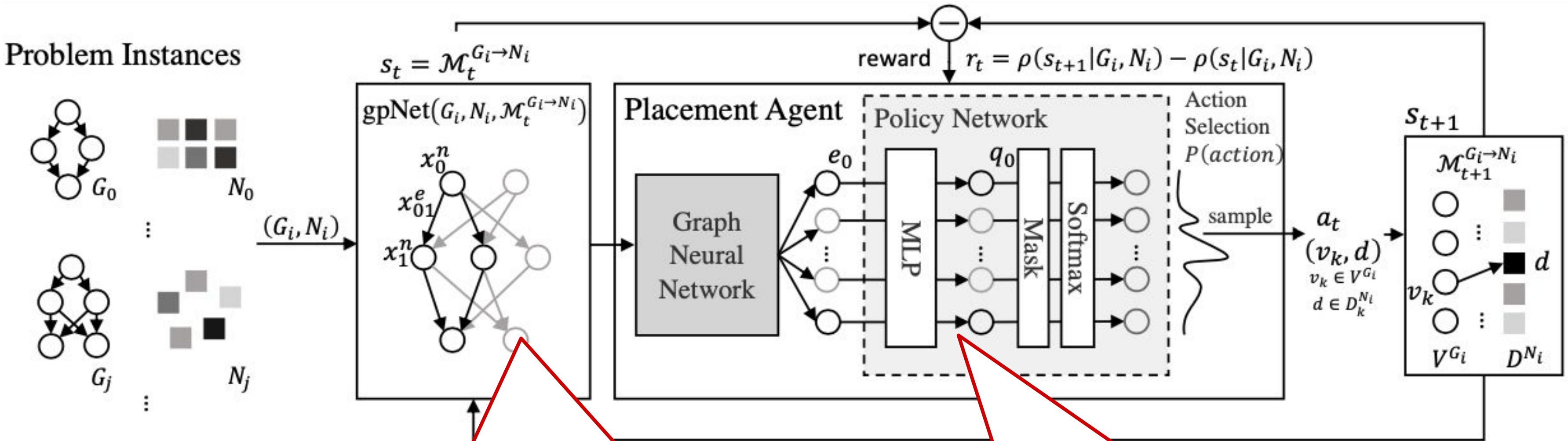
- **State space**
  - set of all feasible placements
- **Action space**
  - set of feasible task and device pairs
  - $a_t = (v_i, d_j)$ place $v_i$ on $d_j$
- **Reward**
  - The performance improvement

$$r_t = \rho(s_{t+1}|G,N) - \rho(s_t|G,N)$$



# GiPH: Framework

**GiPH:** Generalizable Placement with the ability to adapt to dynamic Heterogeneous networks




***gpNet***: a graph representation
- Encode information of an arbitrary task graph and network pair
- Capture all task- and device-related features
- Has a *local graph structure* corresponding to each possible task relocation

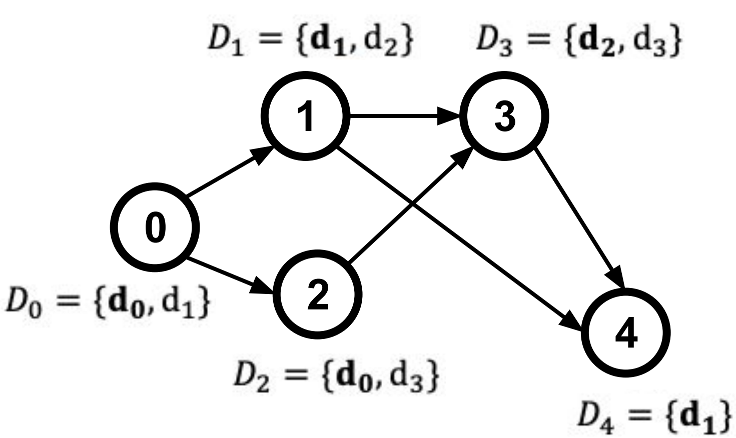
***Placement Agent***: GNN + policy network
- Take a gpNet as input
- *GNN*: calculate an embedding for each action
- *Policy network*: decides an action (i.e., relocating a task) to take

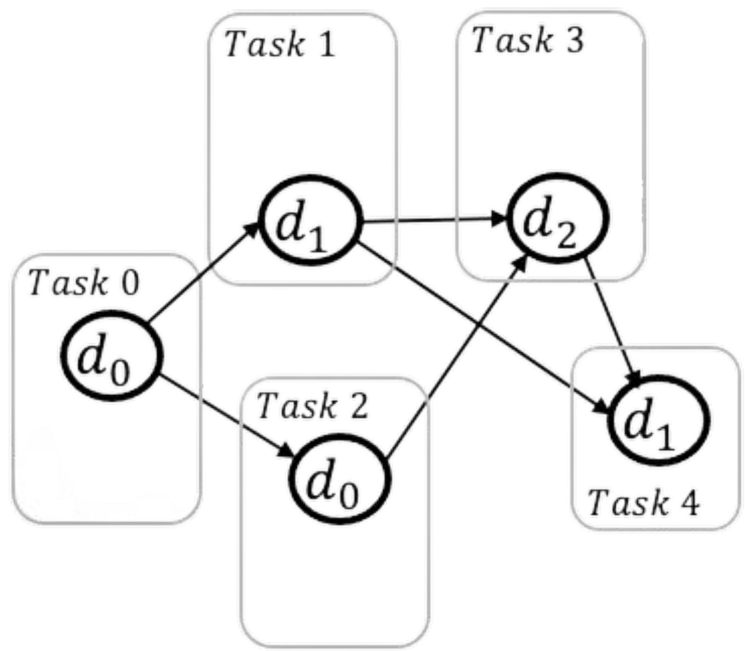
# gpNet Representation

**An efficient graph representation to encode information**

- Each node corresponds to one action
- Local graph structure corresponds to an alternative task placement

Current Placement and Constraints



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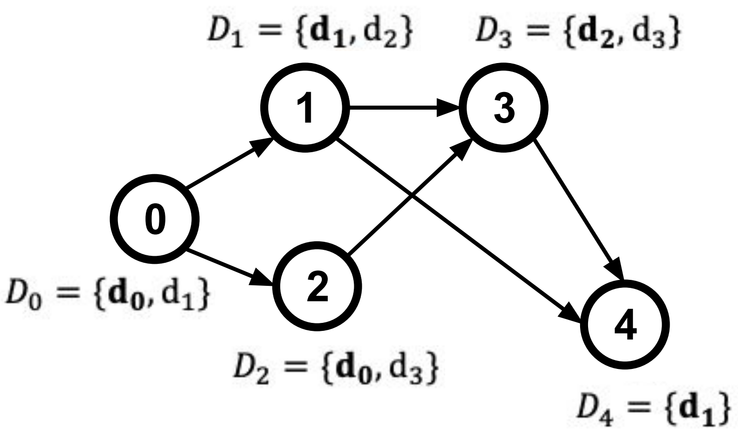


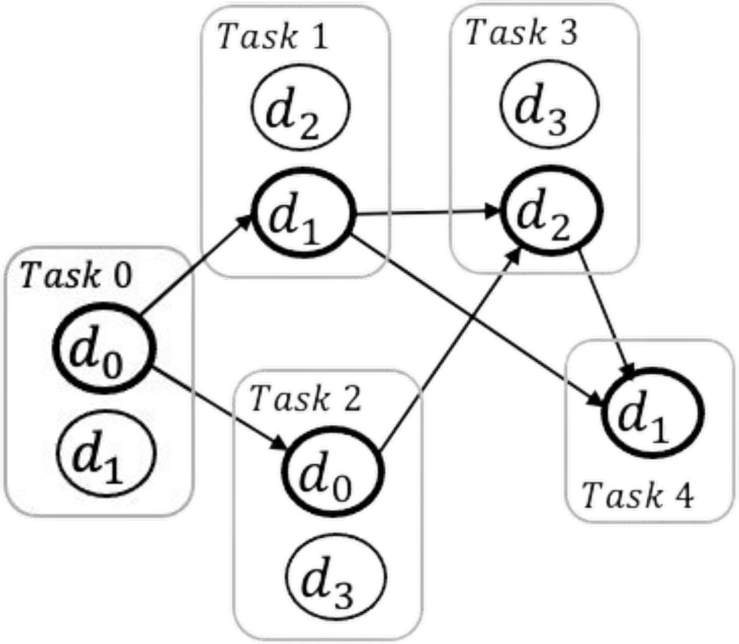

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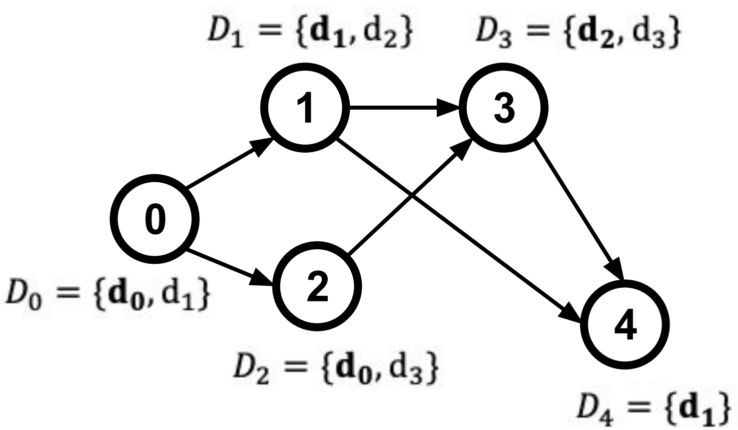
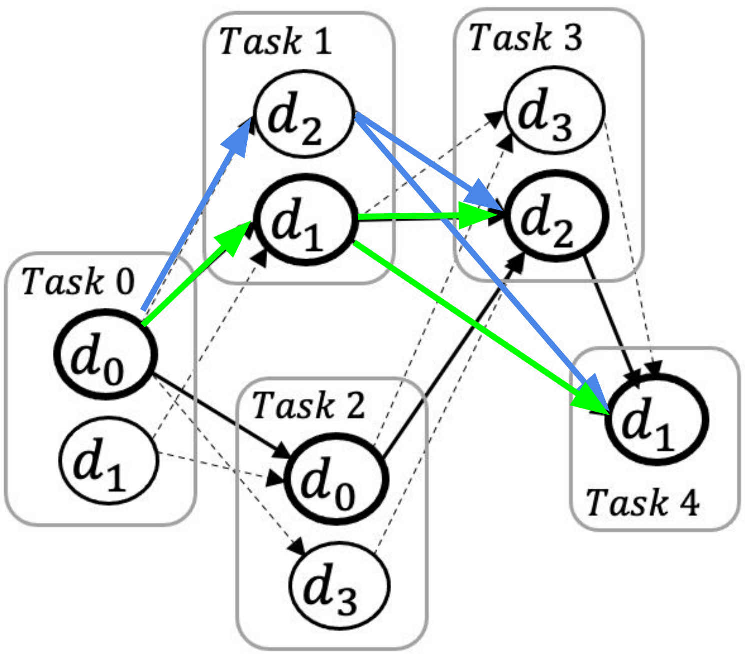
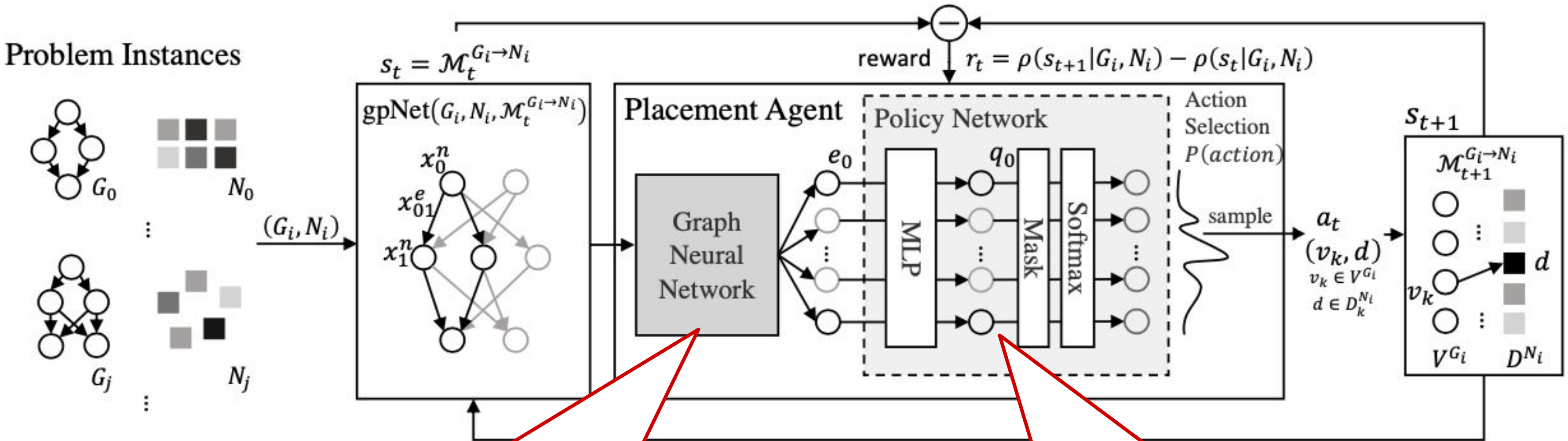



gpNet



# GiPH: Neural Network Design

## Scalable placement policy: GNN + RL policy network




***GNN***: takes a gpNet as input and embeds the placement information as a set of vectors

$$e_u = h_2\left(\sum_{v \in \xi(u)} h_1\left([e_v \,\|\, x_{vu}^e]\right)\right) + x_u^n$$

***RL policy network***: decides the action of re-placing one of the task (placement update step)

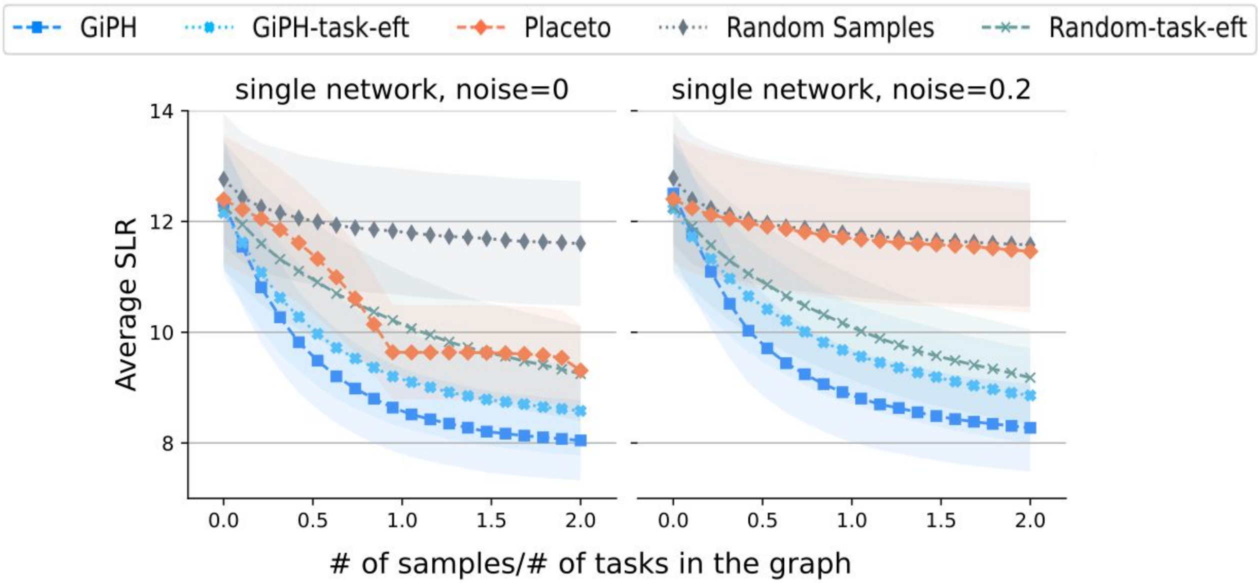
- Score function $q_a = g(e_a)$
- Softmax action selection

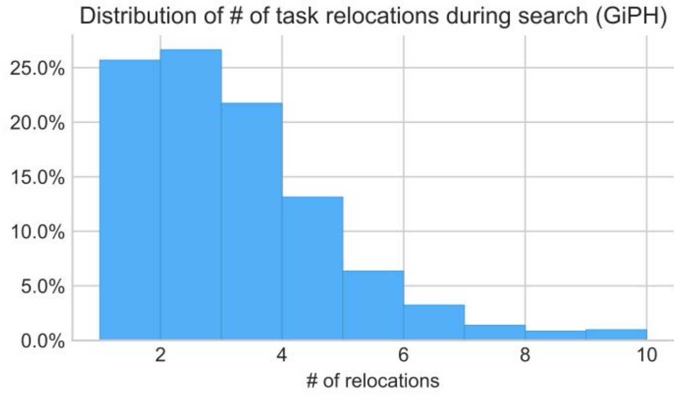
$$\pi(a|s) = \frac{q_a}{\sum_{b \in A} q_b}$$

# Evaluation

- Performance: Schedule Length Ratio (normalized makespan) minimization
- Case Study: Cooperative Sensor Fusion

# Search Efficiency: GiPH vs. Placeto



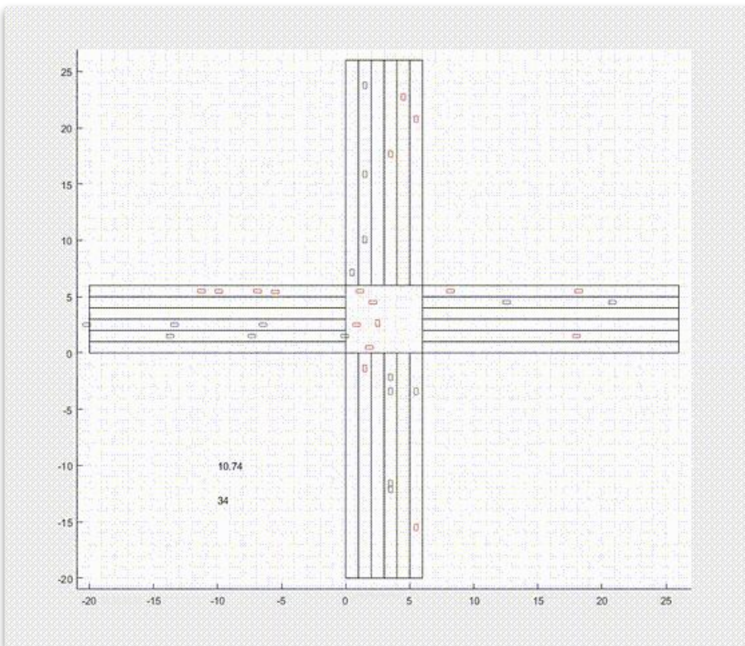



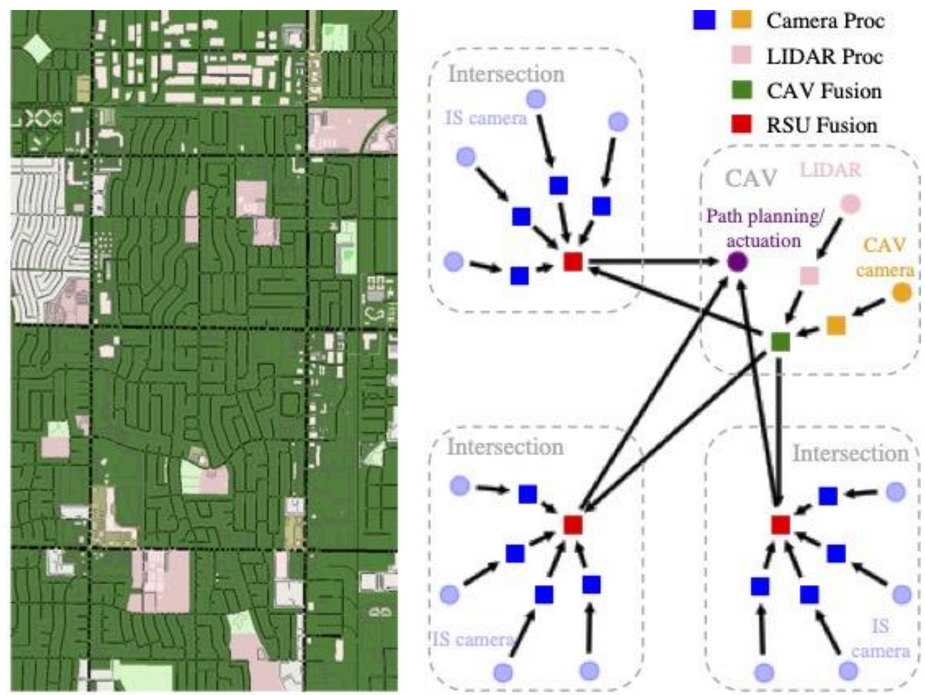

**Placeto**: visit task equally

**GiPH**: adjust the placement of "critical" tasks more frequently within the same number of search steps

# Cooperative Sensor Fusion

- Autonomous driving with roadside units (RSUs), infrastructure camera sensors, and CAVs
- *Simulation of Urban MObility (SUMO)*



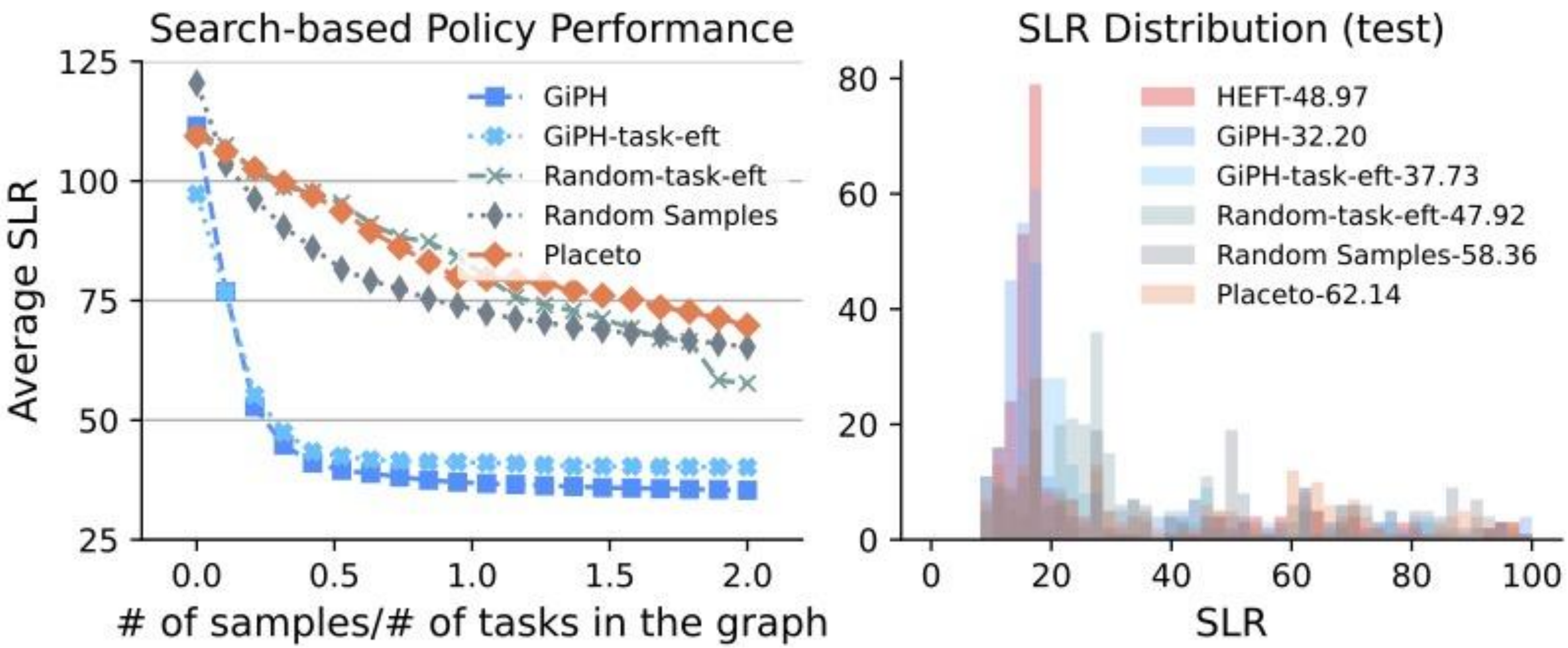




(a)

(b)

a 6-block area in the center of Tempe AZ

# Cooperative Sensor Fusion




- Find ***better*** placement (up to 30.5% lower SLR) with ***higher*** search efficiency than baselines

# Conclusion

- **Formulate the learning problem as a search problem**
  - the policy outputs incremental placement improvement steps
- **Propose GiPH for adaptive placement learning**
  - an RL-based framework for learning ***generalizable*** placement policies for selecting a sequence of placement update steps that ***scale*** to problems of arbitrary size
- **Evaluate on synthetic data and present a case study**
  - GiPH finds placements with up to 30.5% lower SLR, searching up to 3X faster than other search-based placement policies.

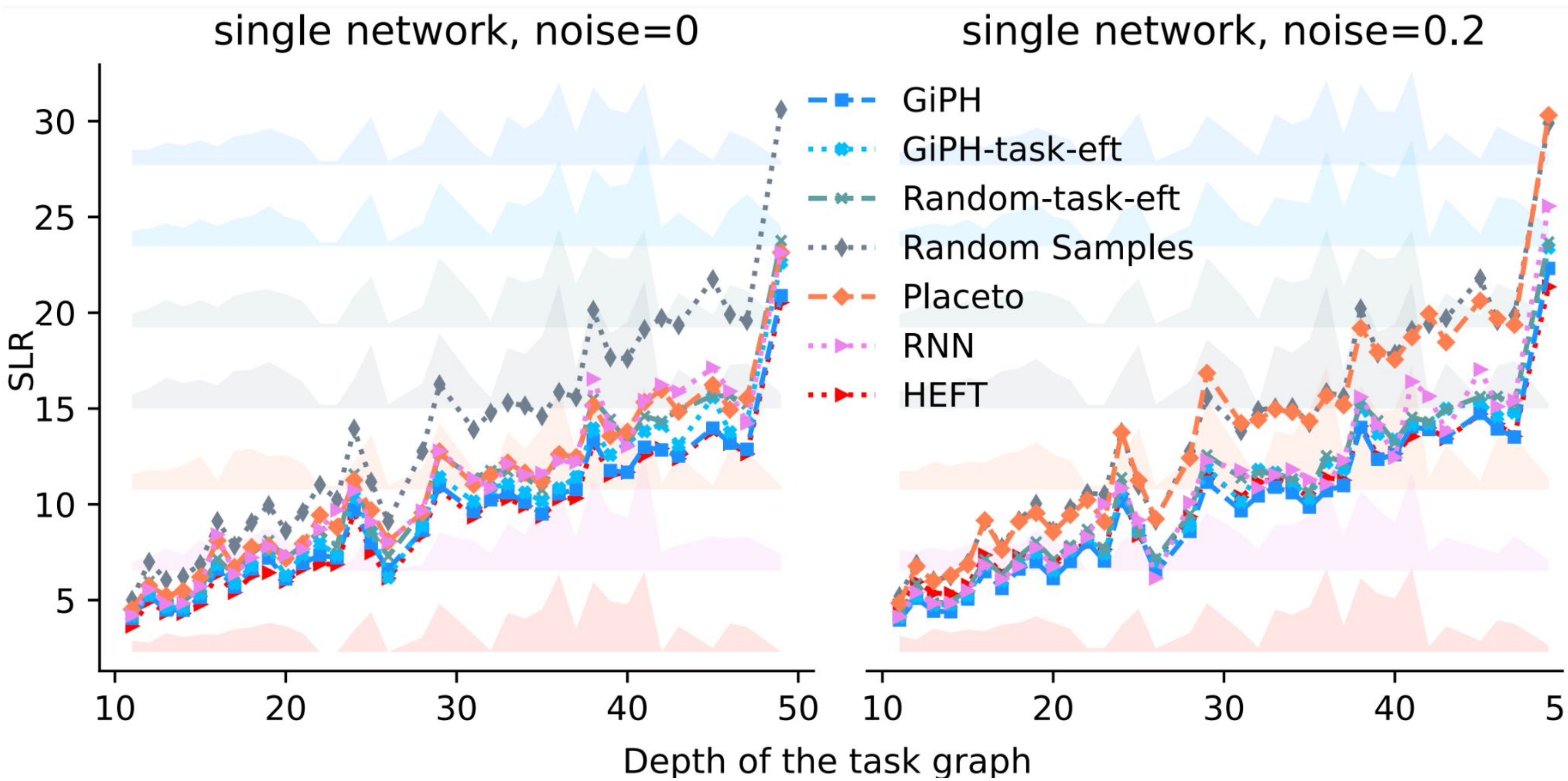
➢ **Next step: real-world deployment**

  - Realistic dynamics that accounts for potential relocation overhead and dynamic application arrivals

# Thanks!

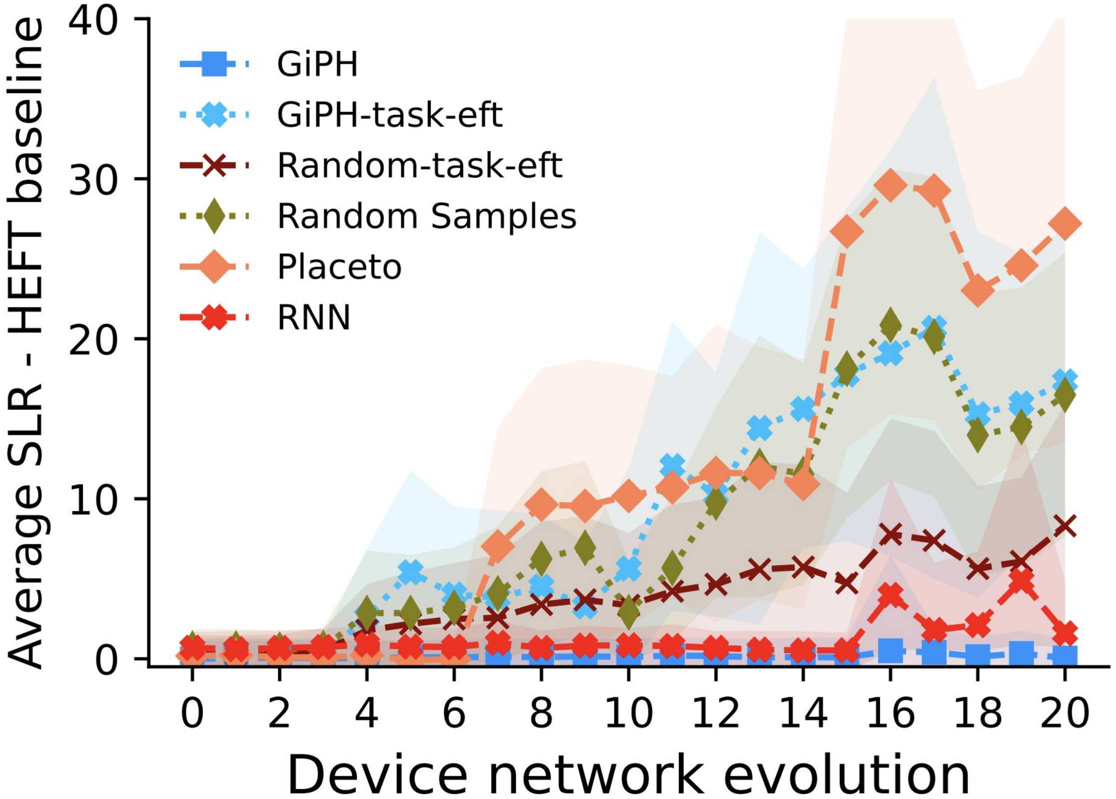
- Code: https://github.com/uidmice/placement-rl
- Contact: yihu@andrew.cmu.edu

# Evaluation: Placement Quality




- GiPH outperforms HEFT on 59% of test cases, and ties on 5.2%.
- RNN-placer trained on individual test cases

# Evaluation: Adaptivity




- Test on a ***changing*** device network
- As the device network changes, GiPH maintains ***stable performance***