MLSys 2023

Carnegie Mellon University

GiPH: Generalizable Placement Learning for Adaptive Heterogeneous Computing

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[2]School of Computing and Augmented Intelligence, ASU
[3]Google

Overview

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

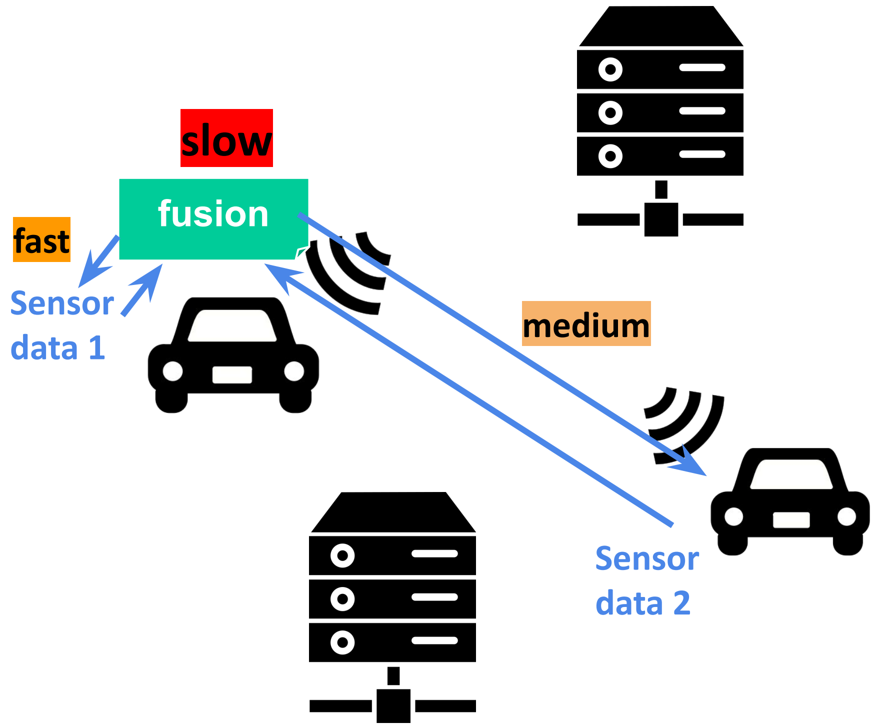
Motivation

- **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

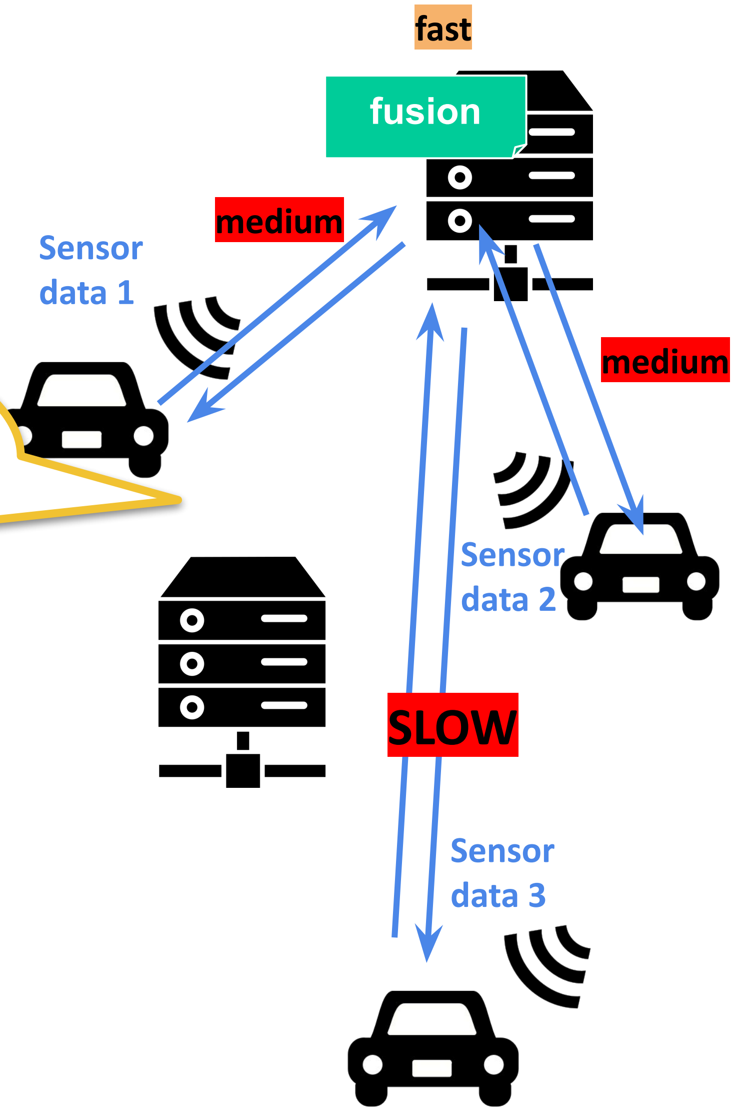
Example: sensor fusion



Placement is the KEY

Example: sensor fusion

Communication and computation time tradeoff (comm/comp capabilities)



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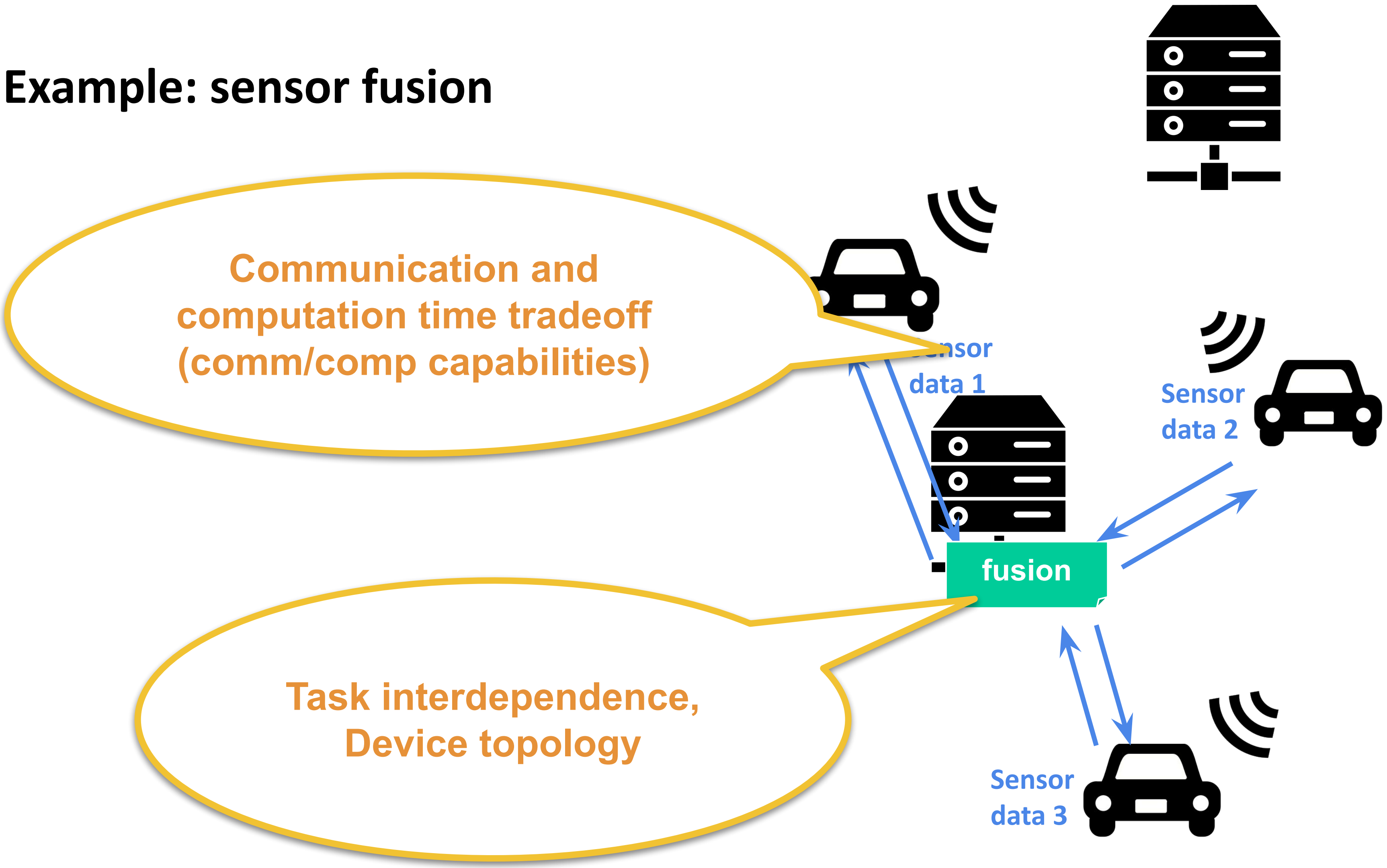
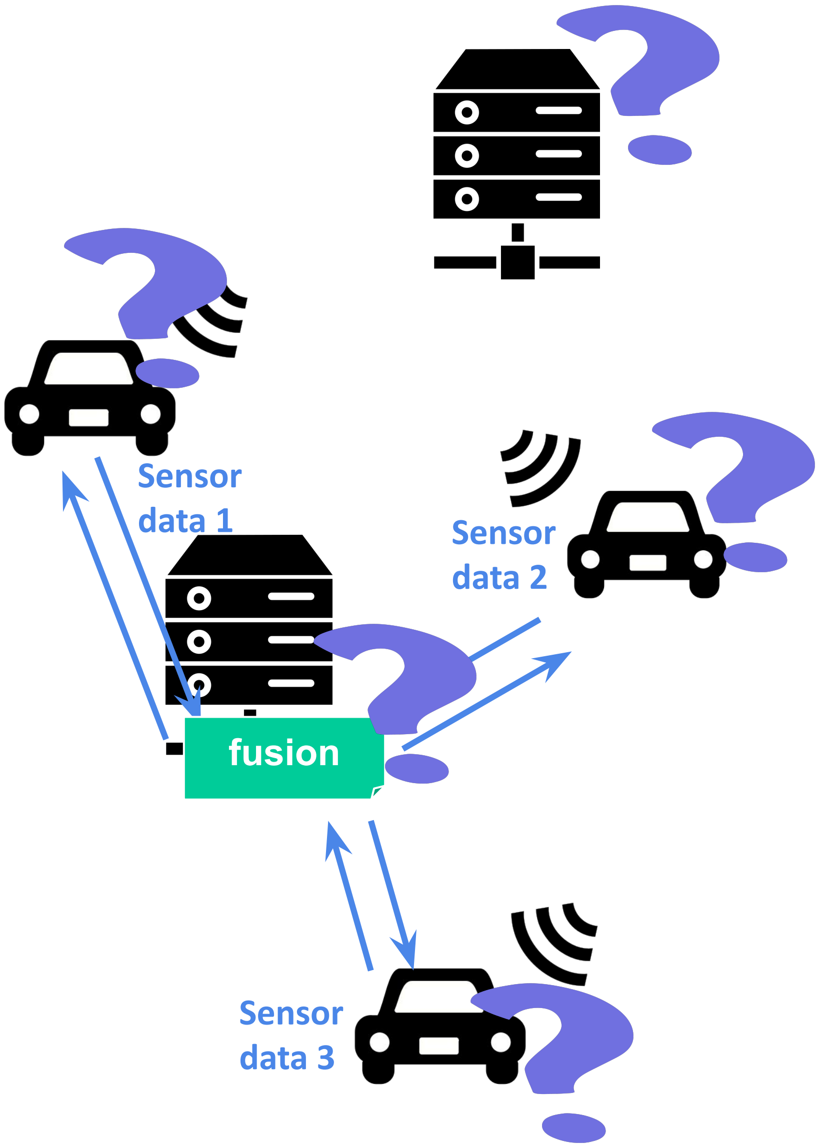


Placement is the KEY

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



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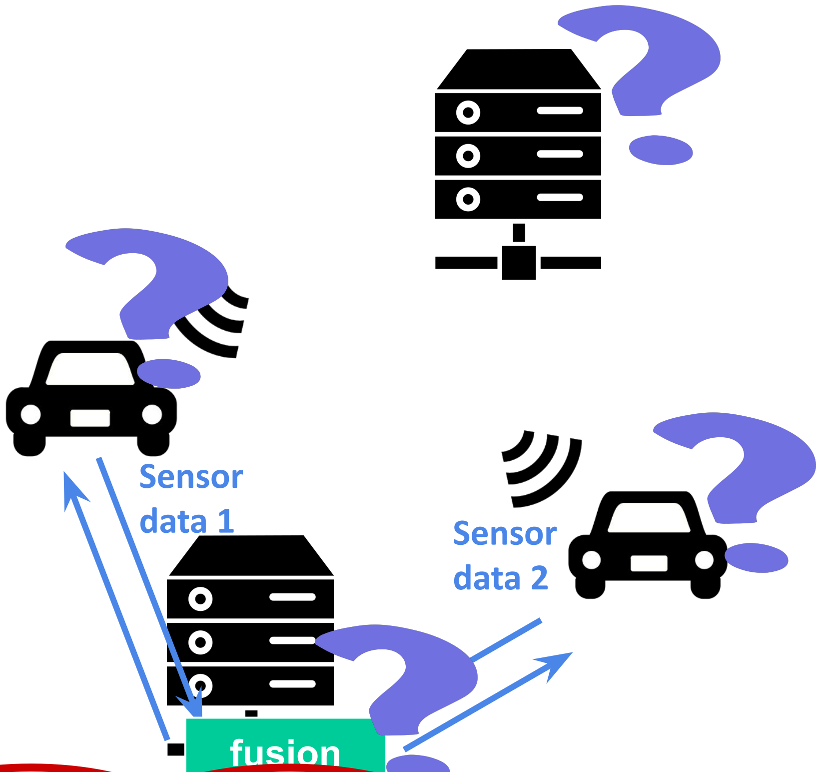

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- Devices can be <u>*volatile*</u>
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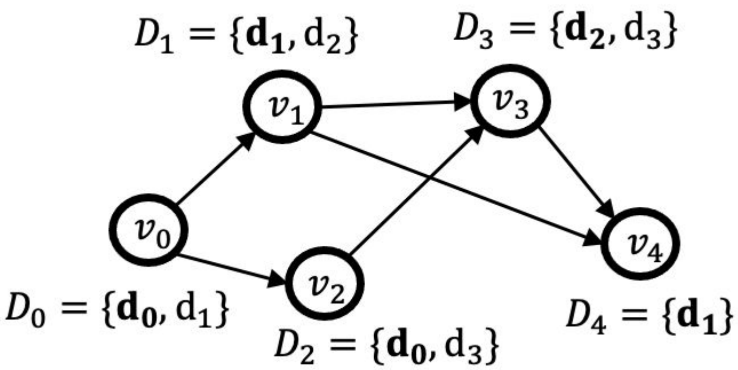
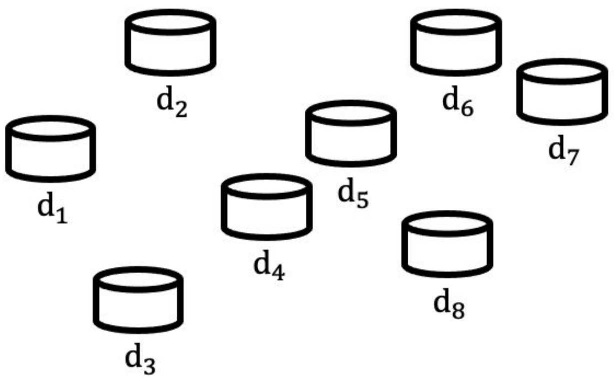
Require a solution that can **scale to different number of devices** and can **efficiently encode information** as the device set changes.

Placement Problem





A compute application *G* (DAG)

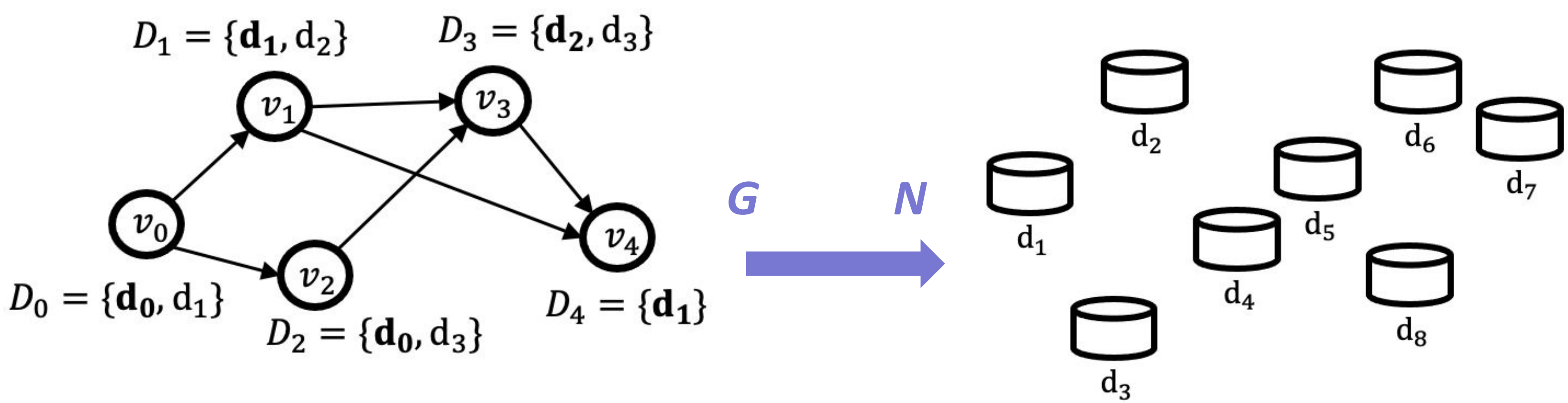
The set of tasks *V*

with placement constraints $D_i \subseteq D$

A target computing network *N*

The set of devices *D*

Placement Problem



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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

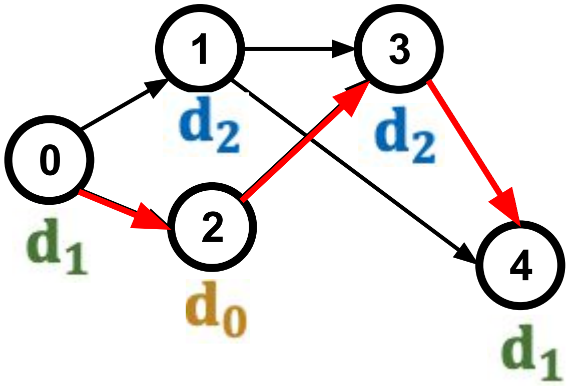
For time-sensitive applications, it is important to minimize the ***completion time***, i.e., makespan

- 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.

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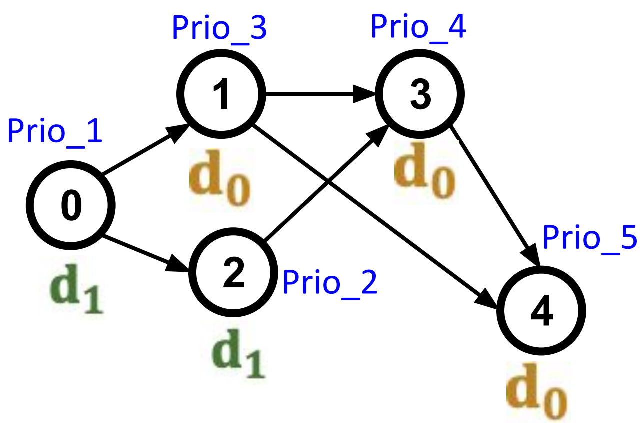

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Related Work: RL-based Device Placement

- **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
  - <u>*Does not generalize to new neural networks/device clusters*</u>

[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.

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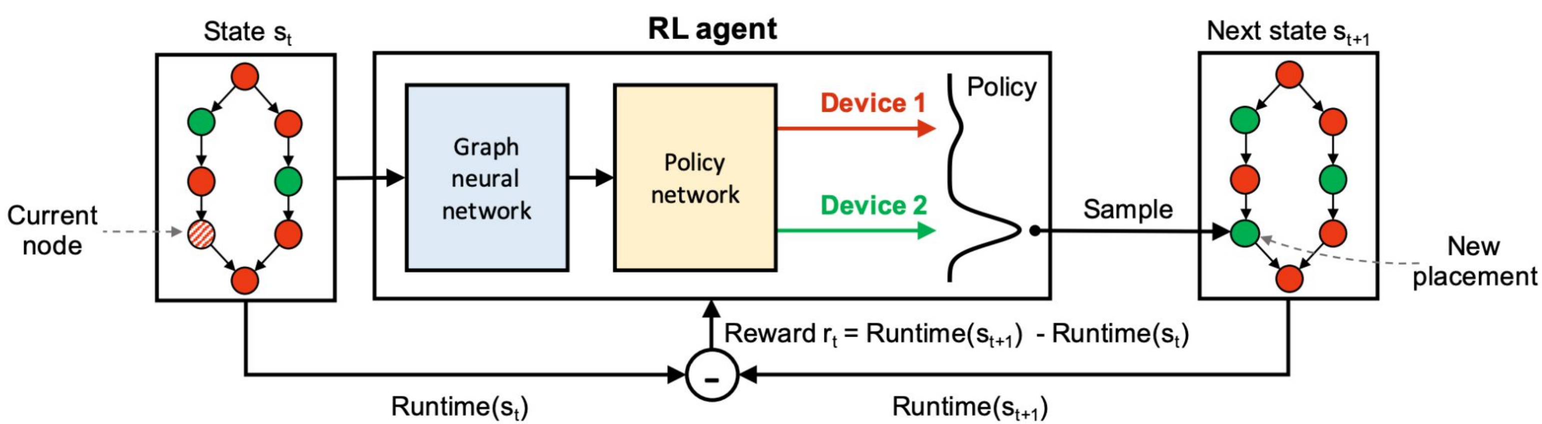
- ***Placeto*[3]**
  - A GNN is used to embed graph-level features
  - *Does not generalize to new device clusters*



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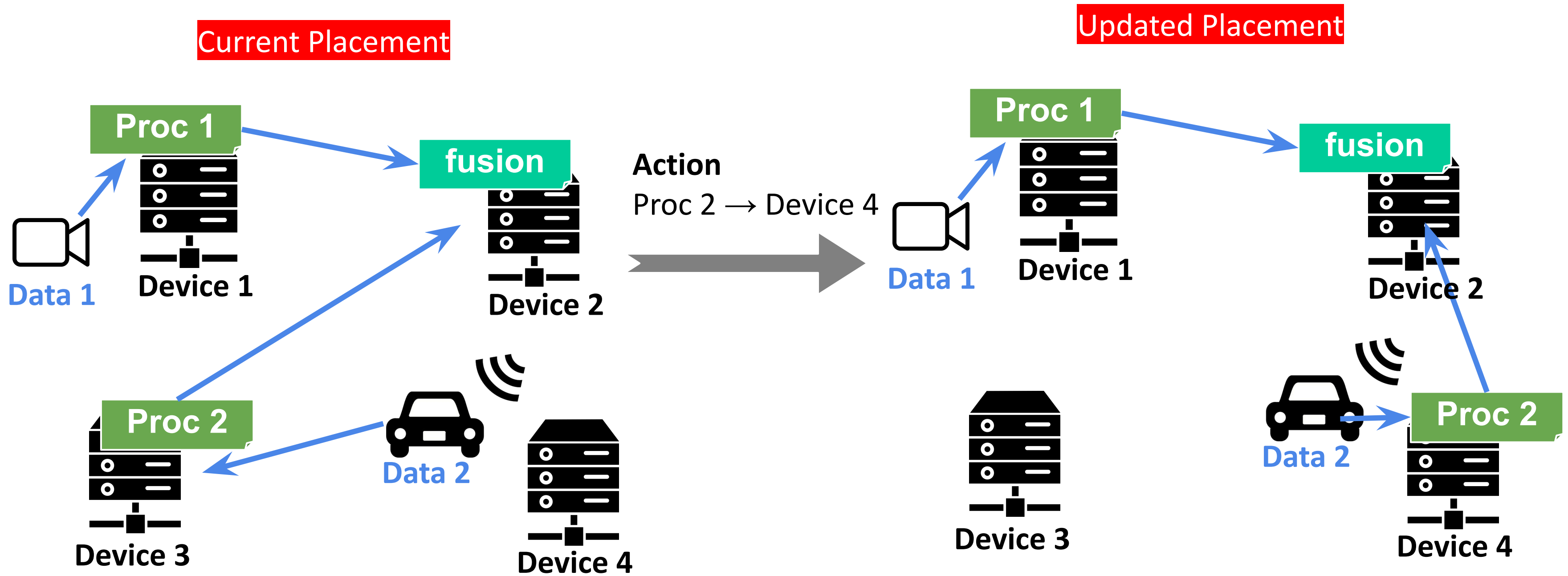
GiPH

- 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)**

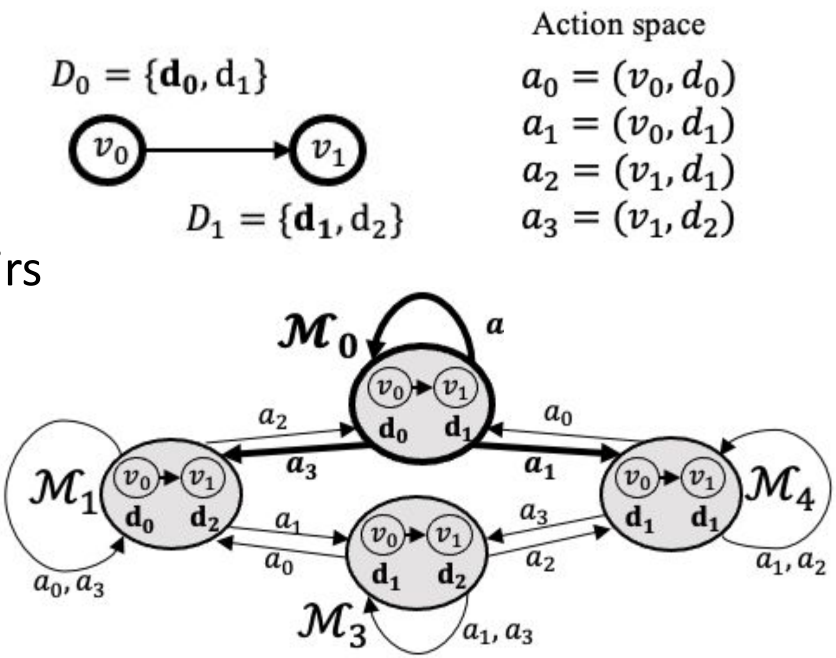


MDP Formalism

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

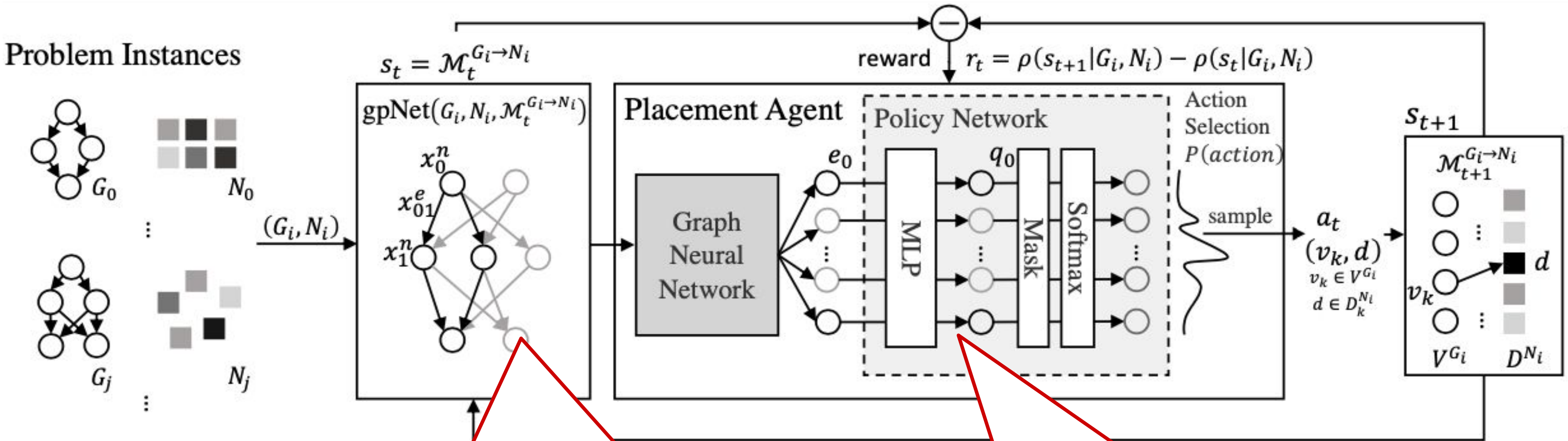
- **State space**
  - set of all feasible placements
- **Action space**
  - set of feasible task and device pairs
  - $a_t = (v_i, d_j)$ place v_i on d_j
- **Reward**
  - The performance improvement

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



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

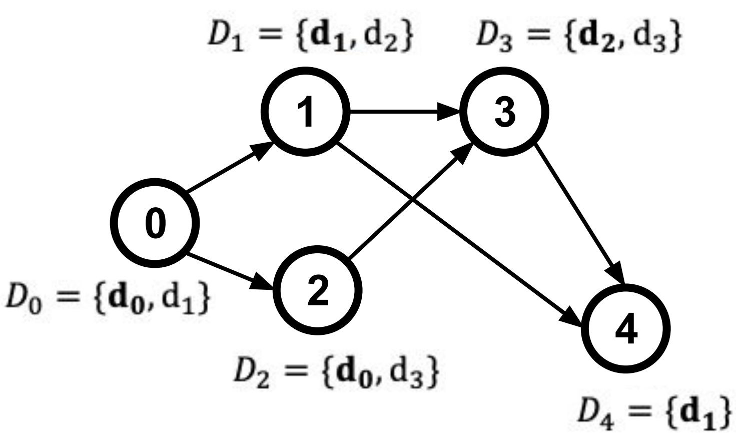
- Take a gpNet as input
- *GNN*: calculate an embedding for each action
- *Policy network*: decides an action (i.e., relocating a task) to take

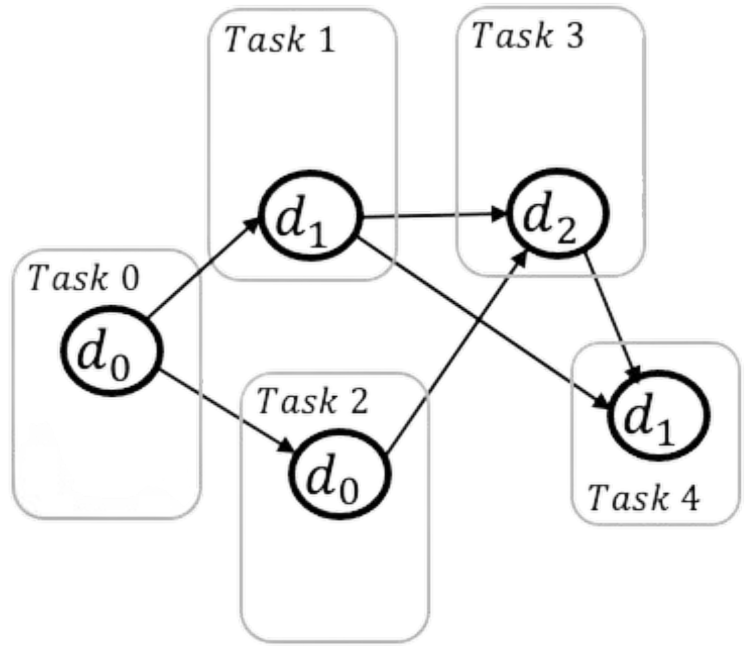
gpNet Representation

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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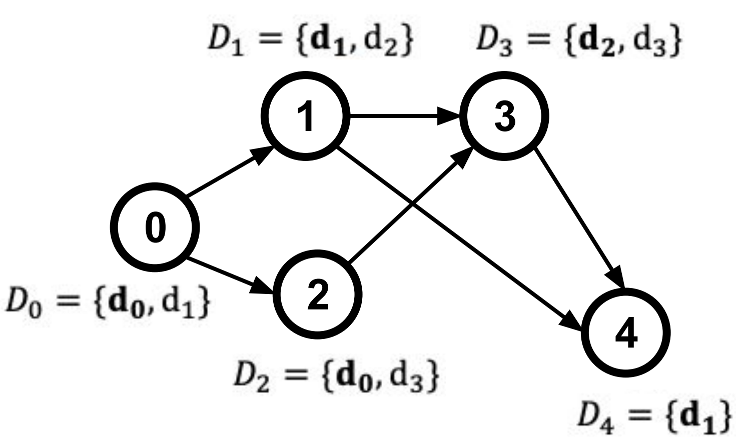

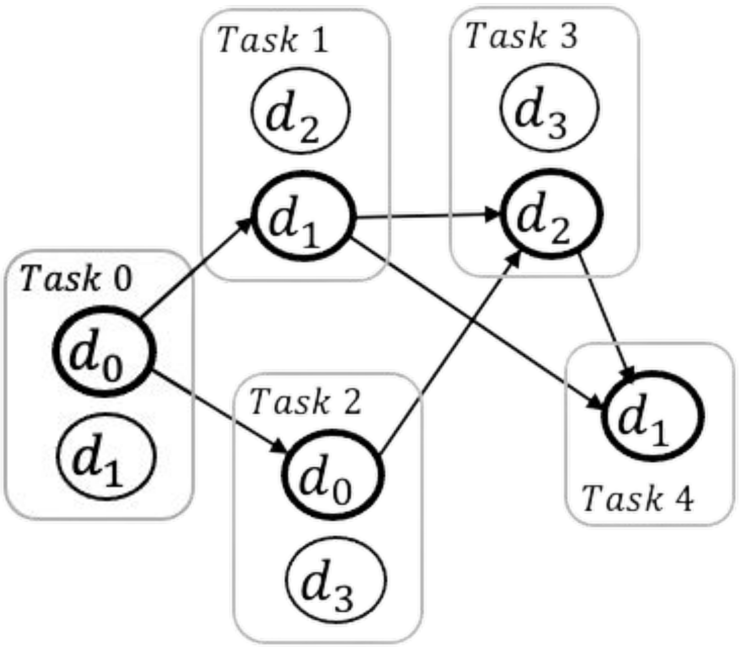

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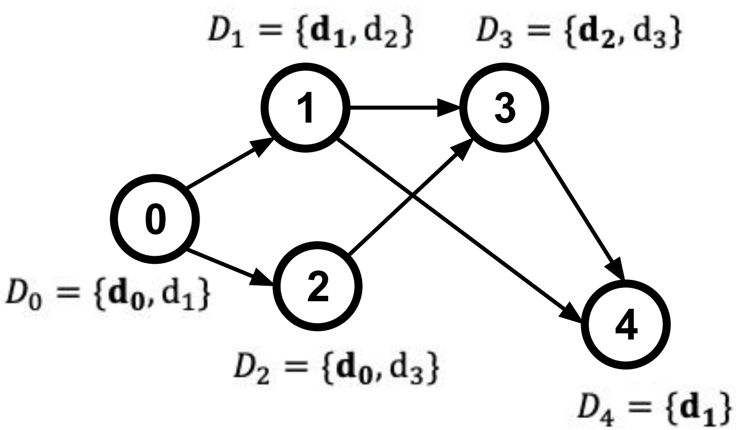
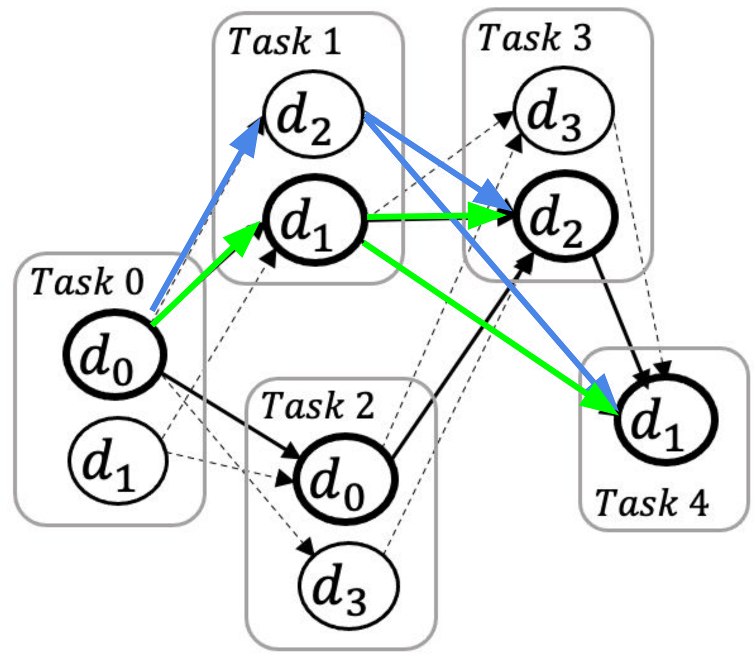
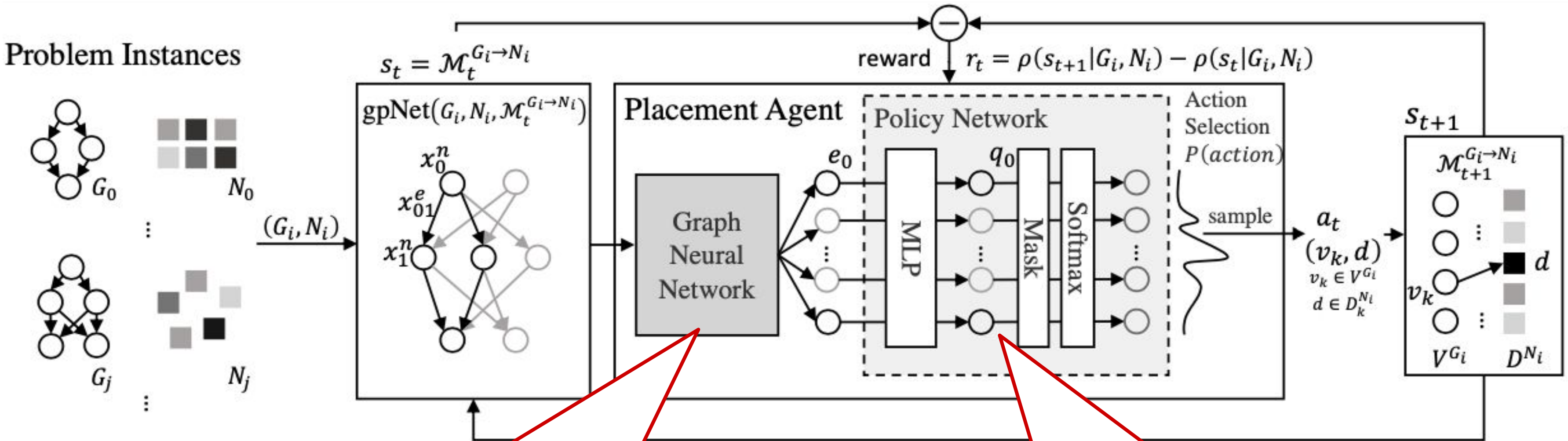


gpNet



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

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

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

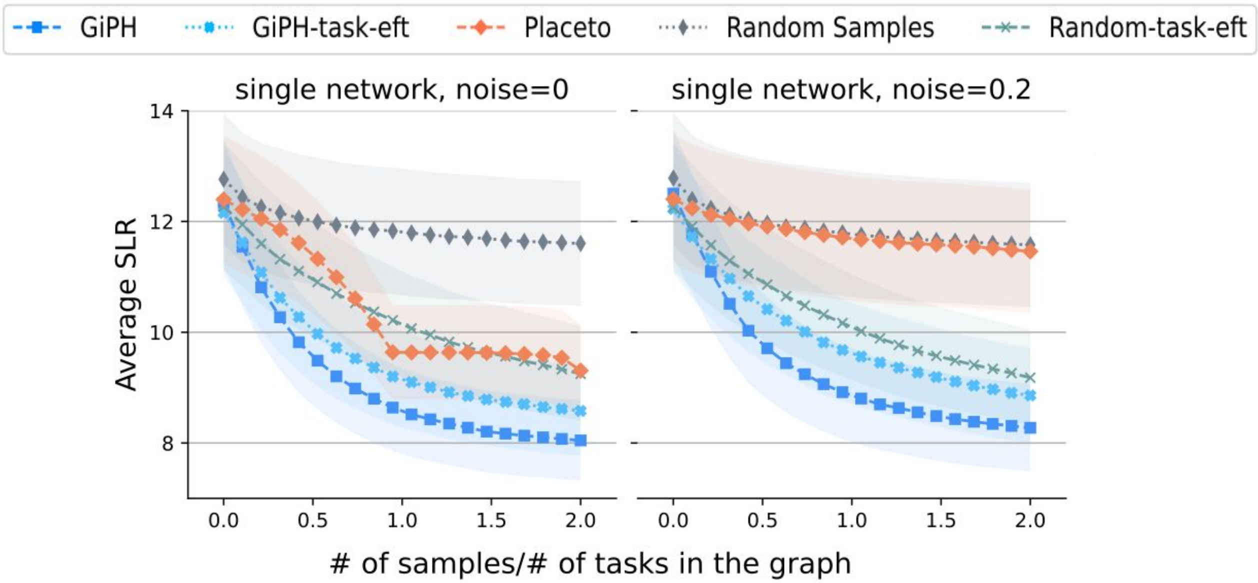
- Score function $q_a = g(e_a)$
- Softmax action selection

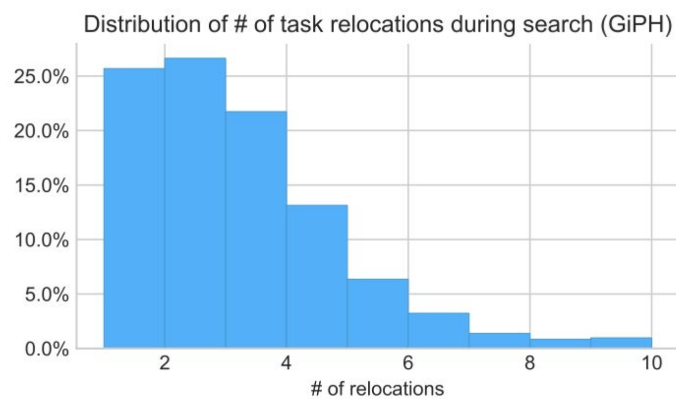
$$\pi(a|s) = \frac{q_a}{\sum_{b \in A} q_b}$$

Evaluation

- Performance: Schedule Length Ratio (normalized makespan) minimization
- Evaluation is done on graphs not in the training dataset
- Case Study: Cooperative Sensor Fusion

Search Efficiency: GiPH vs. Placeto



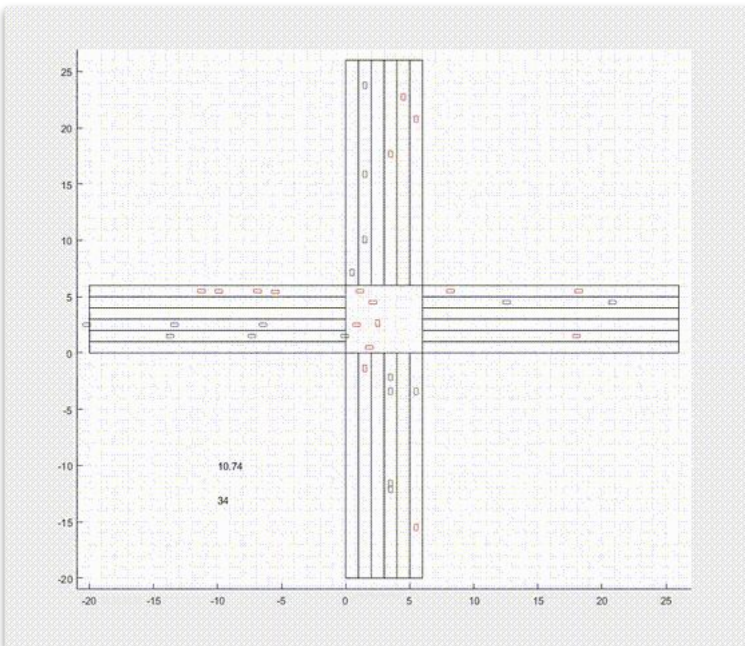


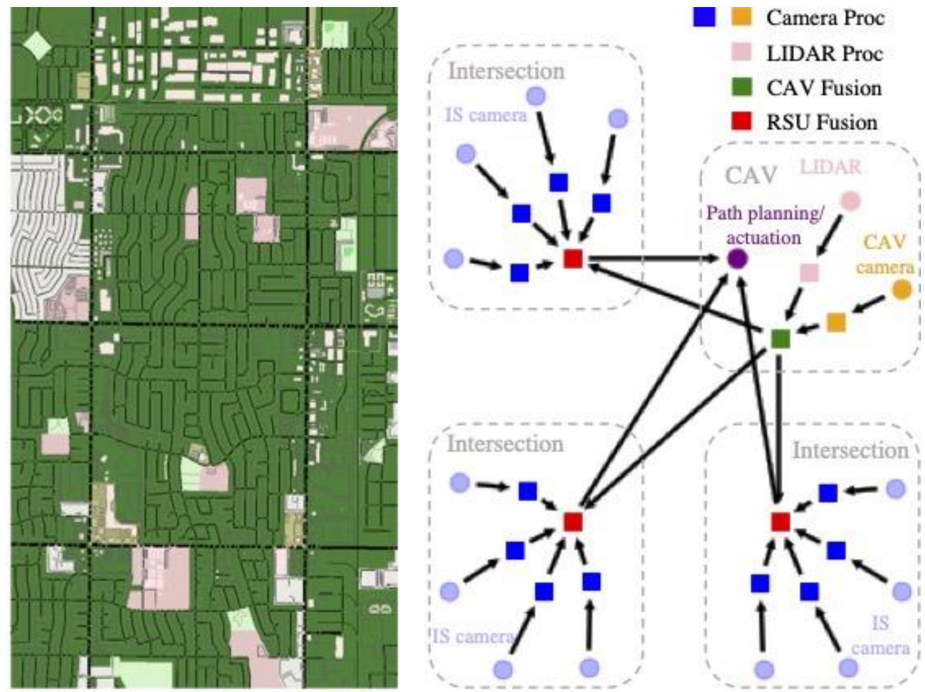
Placeto: visit task equally

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)*

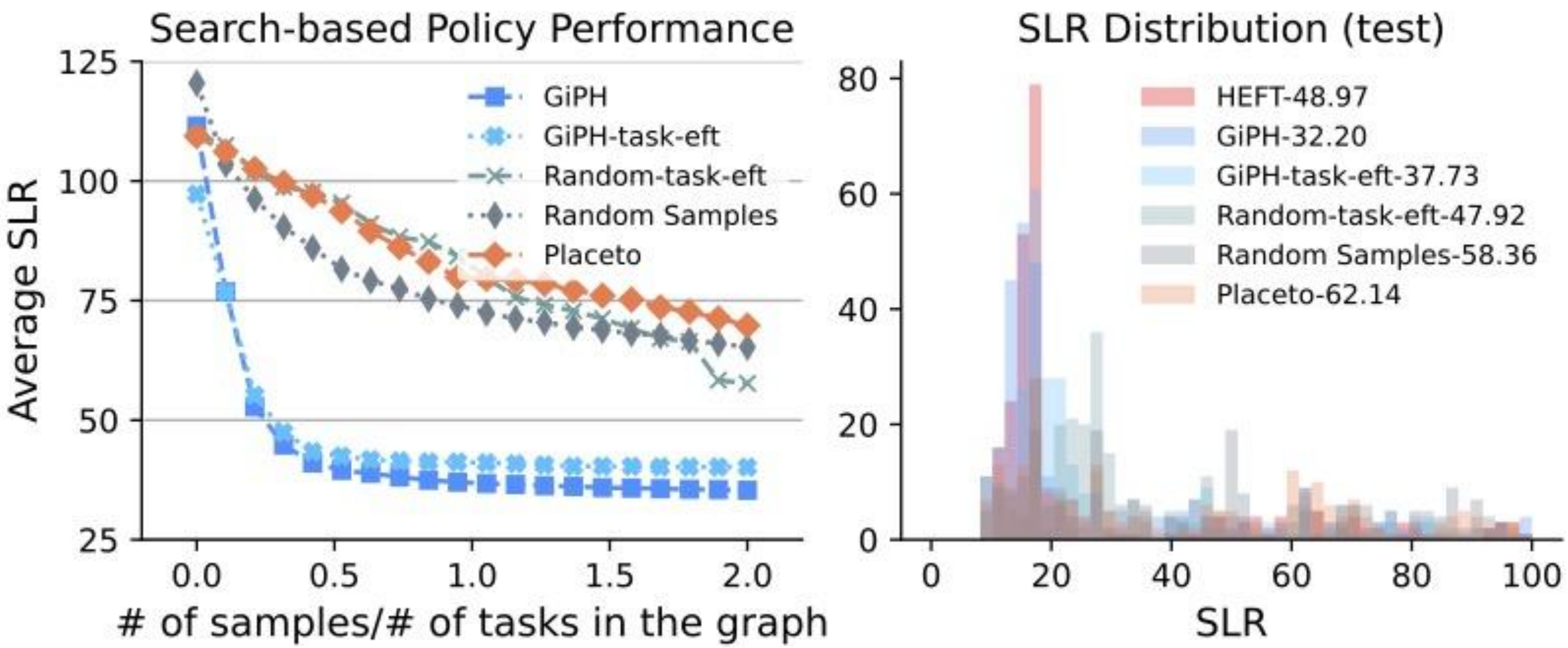




(a) (b)

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

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

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

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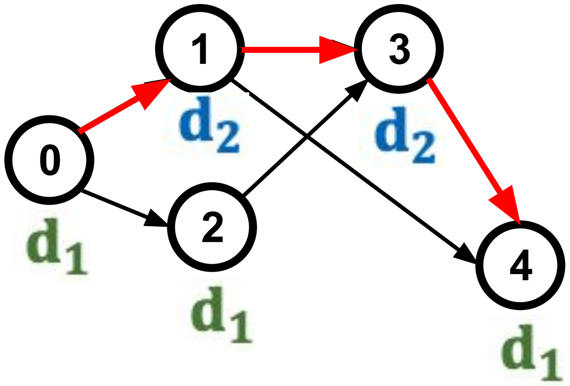
Hard to place the whole graph all at once!

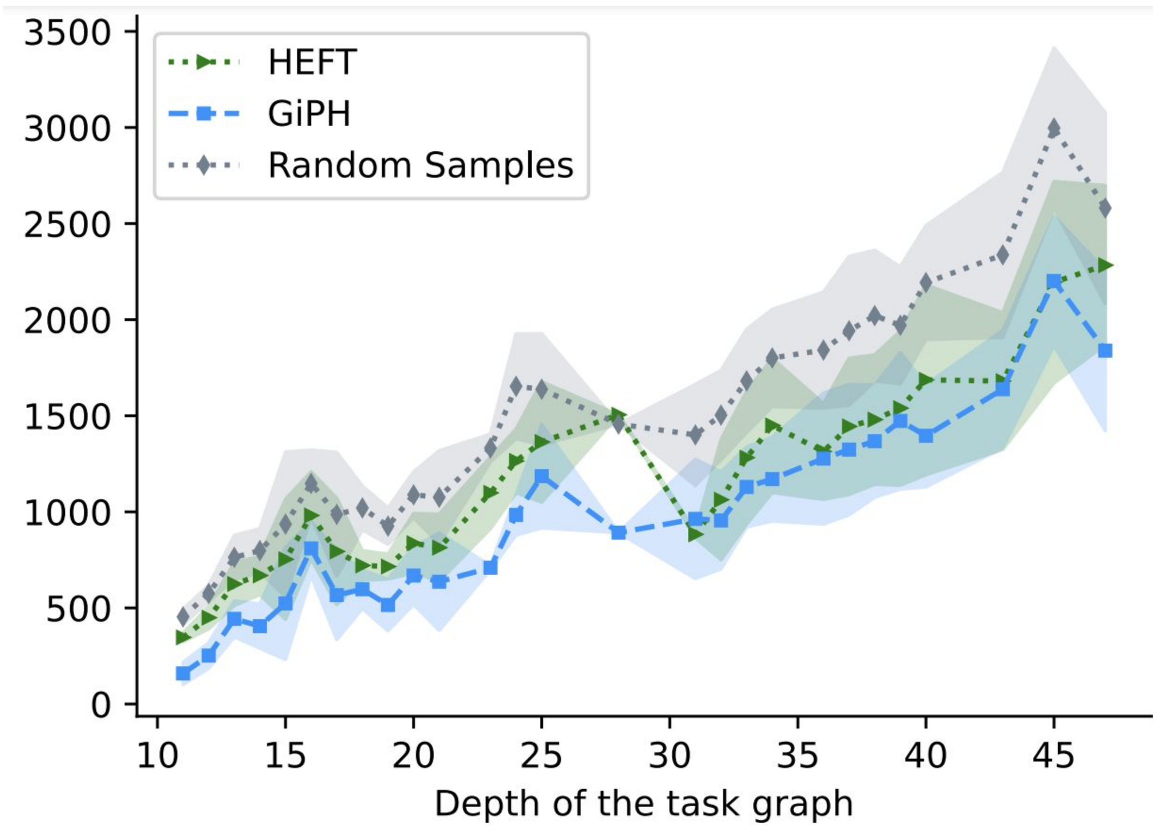


Future Work

- **Consider realistic dynamics**
  - Potential relocation overhead
  - Dynamic application arrival
- **Deploy GiPH on real-world device clusters**
  - Real-world system with centralized administration
- **Extend the work for dynamic task relocation**
  - Time-sensitive task relocation with overhead

Contact: yihu@andrew.cmu.edu

Total Energy Minimization



Challenges

- Combinatorial in nature (NP-hard)
- Devices are heterogeneous
  - Different types
  - Various compute/communication capabilities
- Devices can enter and exit the system
  - The set of devices changes
  - May also change the application graph (data sources)

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

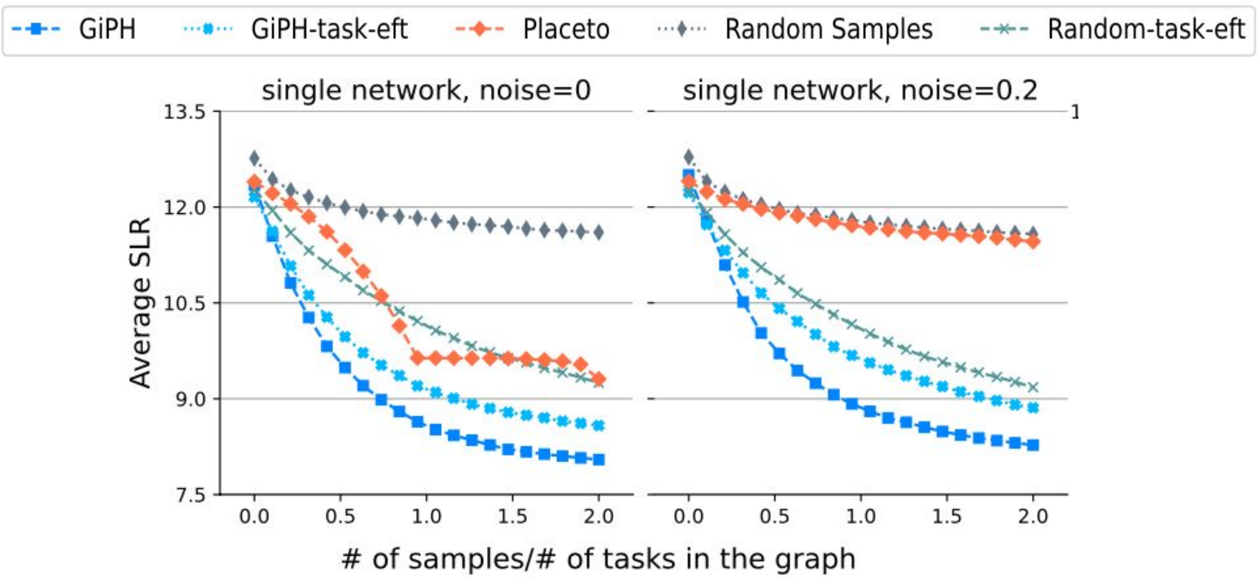
Experiments

- **RL Training: REINFORCE**

$$\theta \leftarrow \theta + \alpha \sum_{t=0}^{T} \gamma^t \nabla_\theta \log \pi_\theta(a_t|s_t) \left(\sum_{t'=t}^{T} \gamma^{t'-t} r_{t'} - b_t \right)$$

- **Baselines:**
  - Random, HEFT, Placeto, RNN-based Placer
  - Random task selection + EFT device selection
  - GiPH task selection + EFT device selection
- **Datasets:**
  - Synthetic data
  - Realistic application traces (case study)
- **Metrics:**
  - Placement quality (Schedule Length Ratio)
  - Placement adaptivity

Evaluation: Search Efficiency



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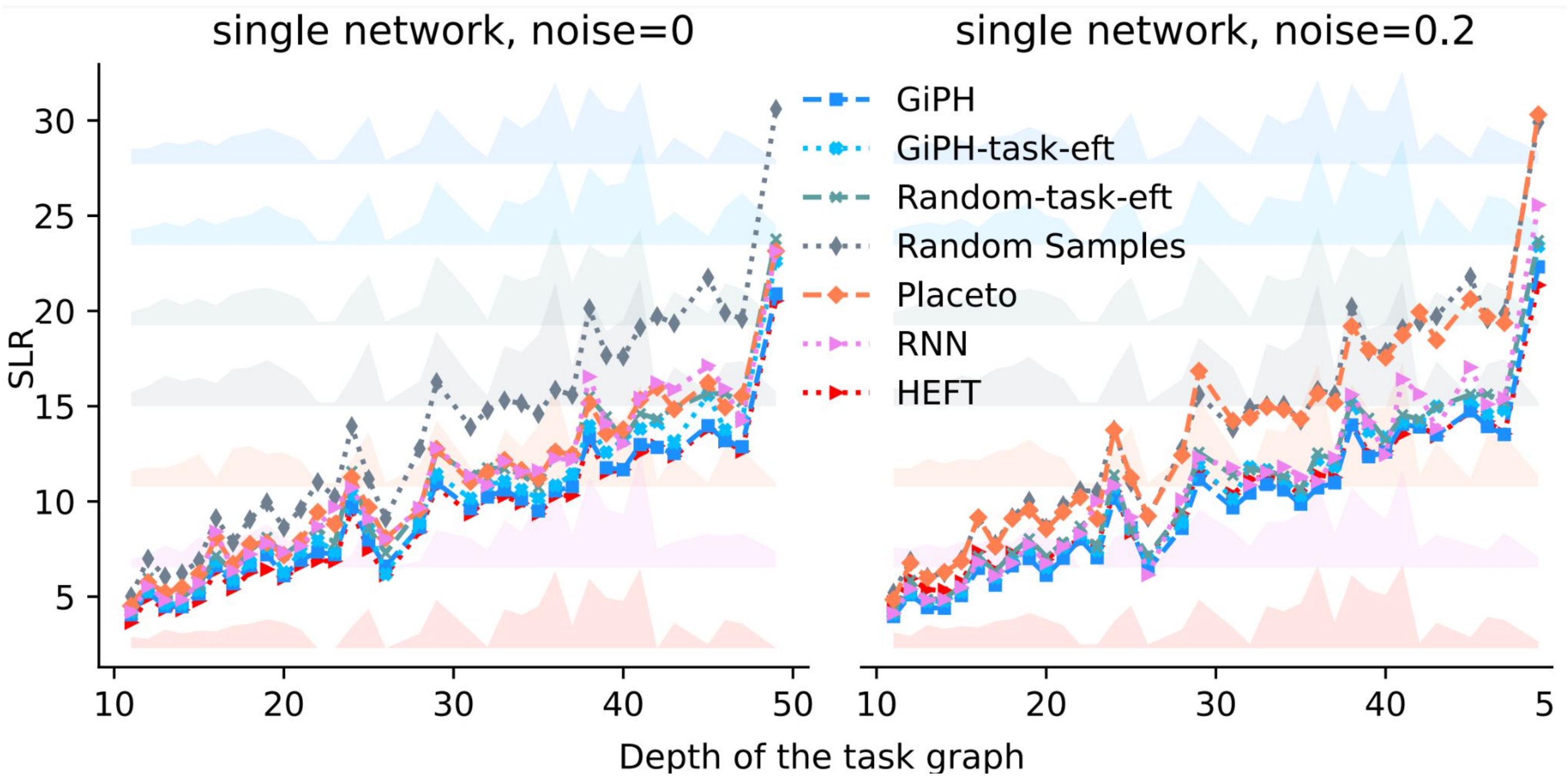
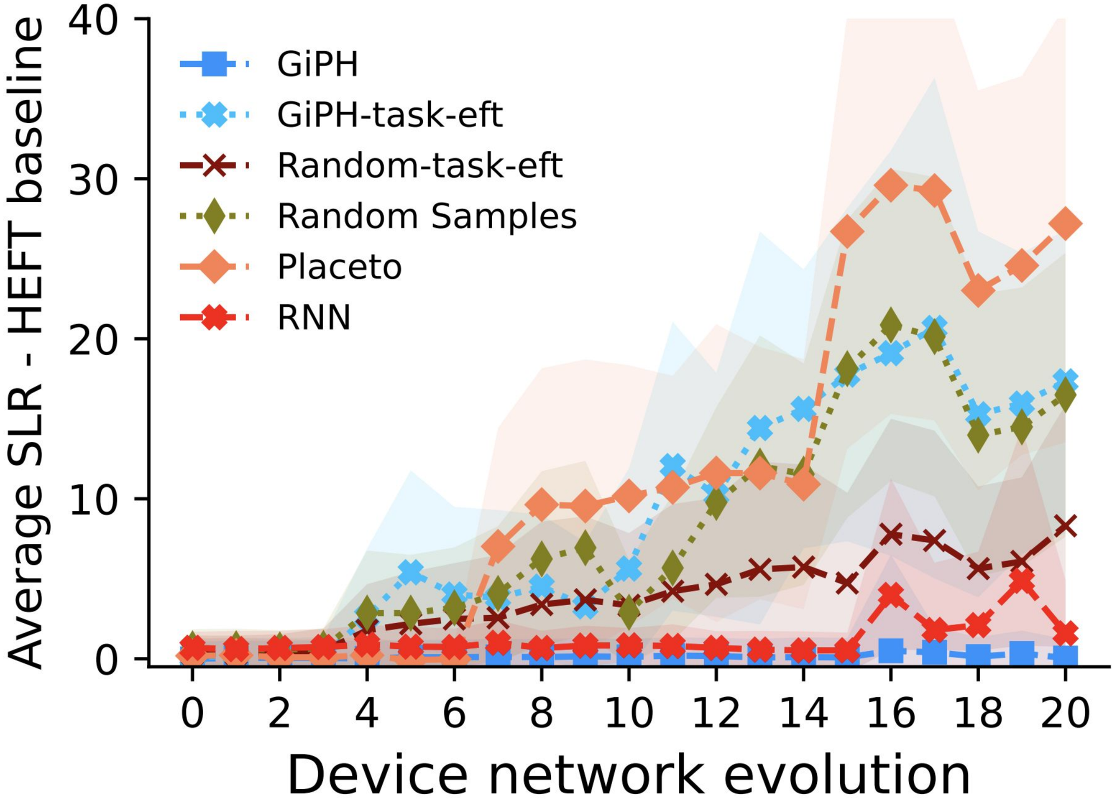
Evaluation: Placement Quality



- 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 ***<u>stable performance</u>***