Deep Reinforcement Learning for Communication Networks

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Abstract

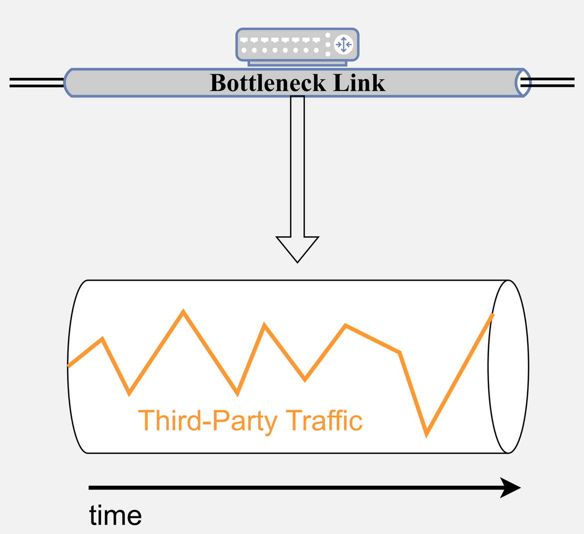
My research aims at optimizing communication tasks in Point-to-Point and Group Communication (GC) networks using Reinforcement Learning (RL) and Multi-Agent RL (MARL). The study initially applied RL for Congestion Control in networks with dynamic link properties from a single agent perspective, yielding competitive results. Then, it focused on the challenge of effective message dissemination in GC networks, by framing a novel game-theoretic formulation and designing methods to solve the task based on MARL and Graph Convolution. Future research will deepen the exploration of MARL in GC tasks and the design of Multi-Agent formulations for Congestion Control.

Research Objectives

- **Exploit the mechanisms underlying communication protocols** to learn what should be communicated and what actions should be taken to optimize a given task.
- Learn agent(s) policies (strategies) **robust to various networking constraints**.
- Investigate methods **suitable to real-world** networking environments to optimize **shared resources** while handling **partial observability** and **highly dynamic scenarios**.

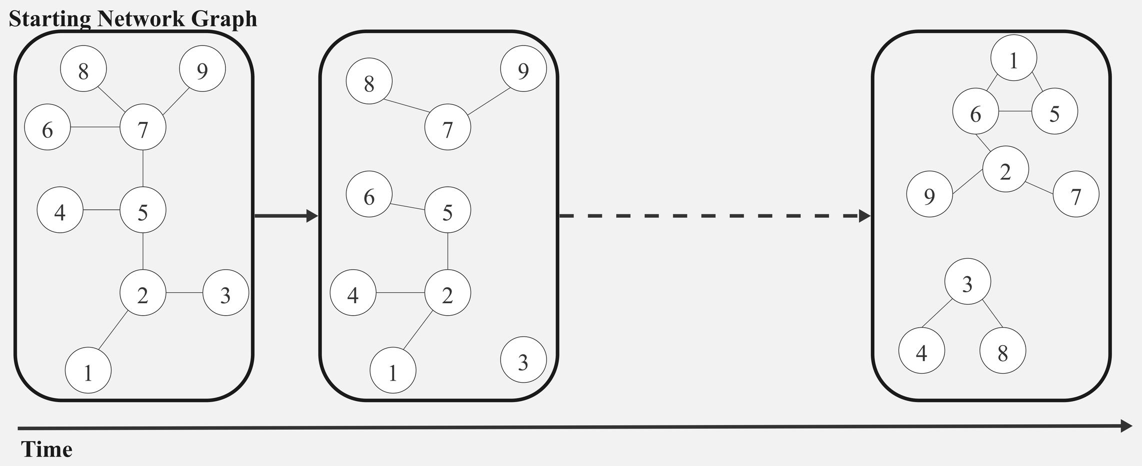
Point-to-Point Communication: Congestion Control

- **Task Objective:** Optimize shared bottleneck utilization while **minimizing queuing delays and retransmissions**.
- **Main Challenge:** The agent has no direct observation of third-party traffic behavior.
- **Motivation:** Current de-facto standard heuristics, eg. TCP Cubic, struggle in unreliable networking scenarios.

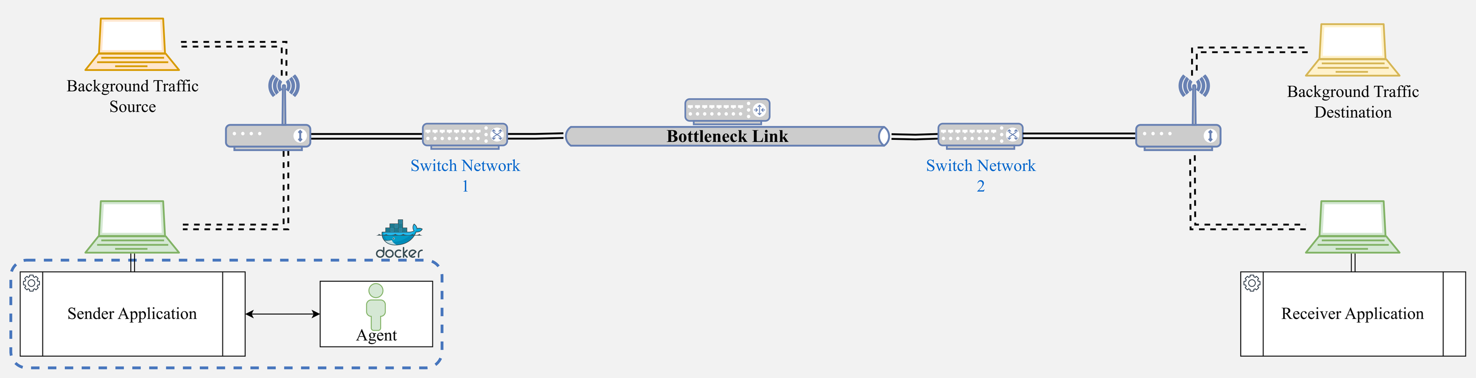


Group Communication: Message Dissemination

- **Task Objective:** Agents should cooperate to **maximize network coverage while minimizing forward actions.**
- **Main Challenge:** Uncontrolled nodes movement and highly dynamic network structure.
- **Motivation:** Current methods employed in Mobile Ad-Hoc Networks (MANETs) struggle when the underlying graph structure quickly changes.



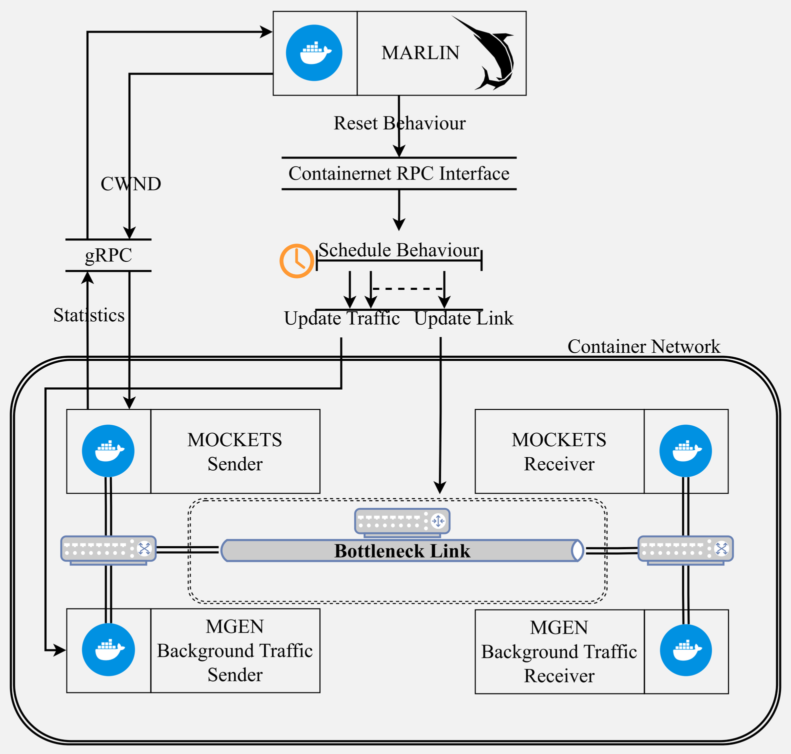
Congestion Control - Real Network



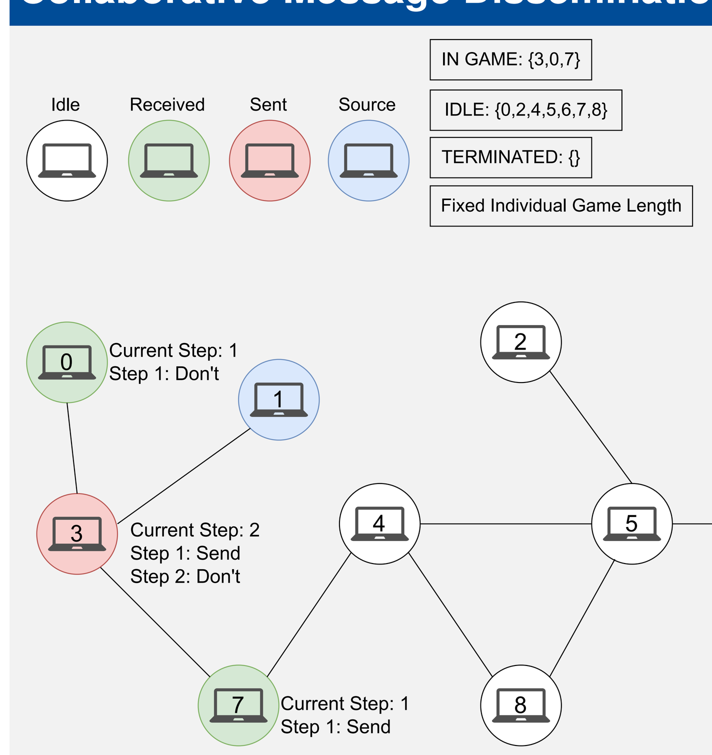
Key Elements:

- **Observation:** History of statistics served by the sender application.
- Focus on **real-world deployment**.
- **Shared bottleneck link** with background traffic patterns injected by unseen entities.
- Agent-Protocol **non-blocking** partnership.
- **Action space:** Continuous $[-1, 1]$
- **Soft-Actor Critic**.

Congestion Control - Containerized Environment



Collaborative Message Dissemination

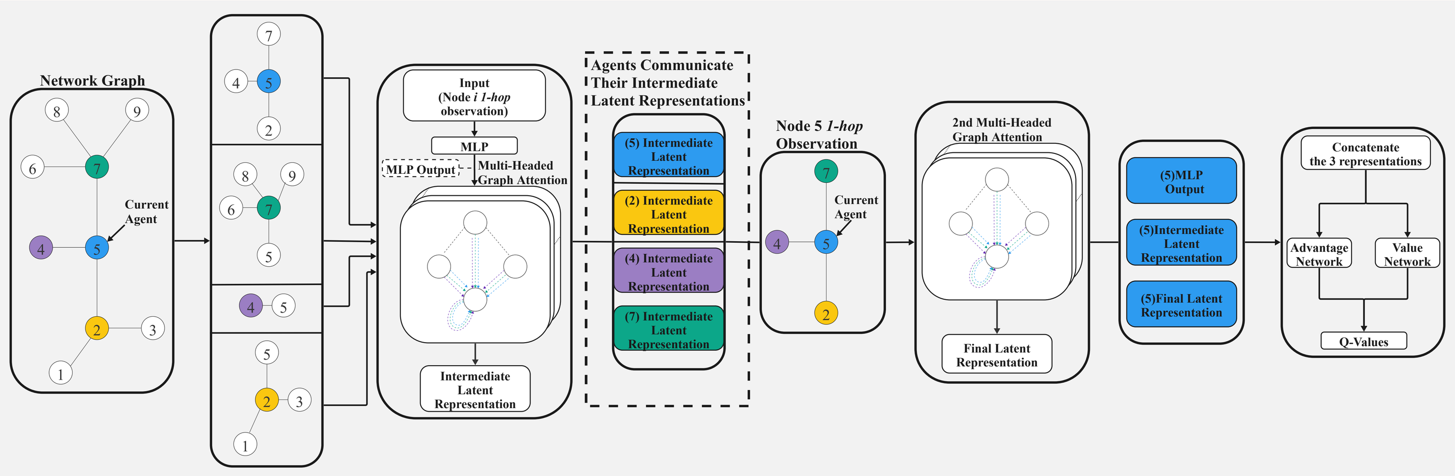


Key Elements:

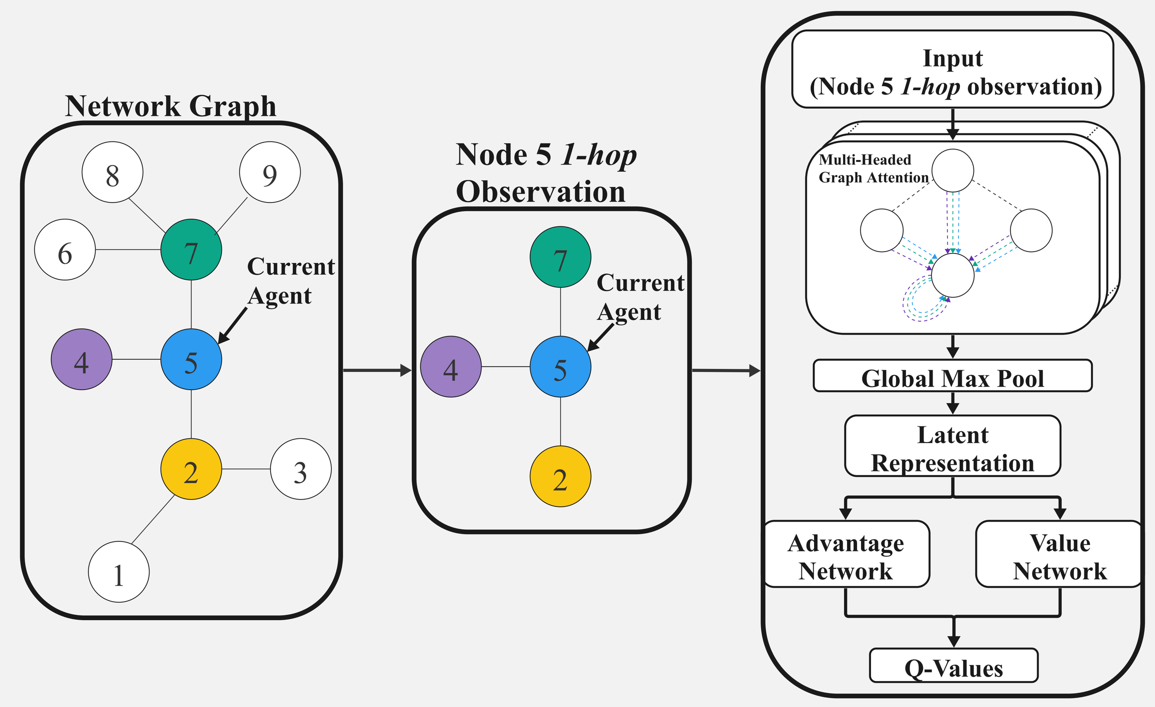
- **Observation:** One-hop neighborhood.
- Agents **become active** once they receive a message and will be active for N steps.
- **Actions:** Forward or stay idle.
- Uncontrolled **dynamic graph behavior**.
- **Graph Convolutional Reinforcement Learning.**
- **Two proposed architectures** with different communication requirements.
- **Encourage cooperation** between neighbors.

$$\mathcal{L}(\theta)=\frac{1}{|\mathcal{B}|}\sum_{\mathcal{B}}\frac{1}{|\mathcal{N}^{+i}_{i,\mathcal{I}_a(t)}|}\sum_{j\in\mathcal{N}^{+i}_{i,\mathcal{I}_a(t)}}\left(y_t^j - Q(o^j,a^j;\theta)\right)^2.$$

Collaborative Message Dissemination - Local-DyAN

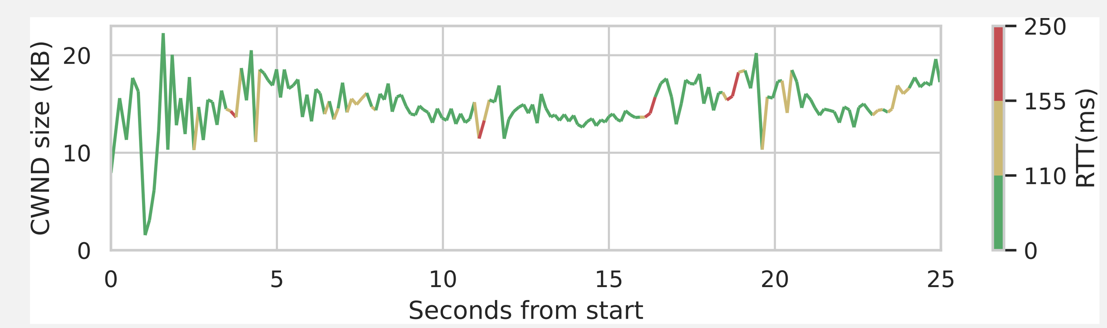


Collaborative Message Dissemination - Hyperlocal-DyAN



Some Results - Congestion Control

- Main Achievements:
  - Outperforms heuristics in unreliable scenarios showing a more efficient utilization of the bottleneck links'.
  - Lower impact on nominal link delays and retransmissions.
- Main Limitation: Conservative behavior.



Some Results - Collaborative Message Dissemination

- Main Achievements:
  - Outperforms both a standard heuristic (MPR) deployed in real-world protocols and a graph-based MARL baseline.
  - Keeps nodes anonymous and is independent of the number of nodes present during training.
- Main Limitation: Existing heuristics are a better choice in static scenarios.

Metric	L-DyAN	HL-DyAN	MPR Heuristic	DGN
MSGs	**24.35** ± **5.69**	**35.12** ± **6.23**	13.62 ± 6.47	6.92 ± 3.88
CVG.	**86.50%** ± **18.01**	**90.02%** ± **15.46**	55.12% ± 22.99	37.02% ± 20.71

Results report mean and standard deviation over multiple scenarios.

Future Work

- **Focus:** Group Communication tasks and Multi-Agent environments for Congestion Control.
- **Learn when to share** information and/or the next action should be taken.
- Integrate and optimize **networking components** to the Collaborative Message Dissemination environment.

Anticipated Contributions

Through real-world evaluations, the outcomes of this research aim to merge the realms of communication protocols and MARL, offering novel models for designing MARL agents suitable for network environments. The integration of real-world evaluations will further solidify the practical relevance and applicability of the devised solutions.