

UE20CS302 – Machine Intelligence

Machine Intelligence – MINI Project

Time Optimized Federated Reinforcement Learning



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Problem Statement

Develop a new architecture for federation in an IoT network to distribute the agents and their search spaces among the nodes such that the total training time is minimized for a reinforcement learning model. We propose doing this by modeling the network as a complete weighted directed graph and generating a minimum spanning tree from the graph by taking the ping between all pairs of devices as the weights for the edges.

This concept has use cases in many different scenarios, especially in situations involving robot swarms for simultaneous localization and mapping.

The challenge here will lie in tuning this architecture to produce an aggregated Q-Table such that the RL model operates at a high level of accuracy.

Application and Uses

APPLICATION

1. Robotic swarms for quick simultaneous localization & mapping
2. Cross node-type collaboration in learning identical environments

USES

1. Autonomous UAV-UGV systems
2. Legged robot swarm locomotion

Scope and Novelty

Scope

1. Generalized algorithm for federating RL use cases
2. MQTT network optimization

Novelty

1. Minimum spanning tree generation for optimized aggregation times
2. GPU multithreading to accommodate multiple agents on a single machine

Literature Survey (2 papers by Student 1)

Title of the paper	Year of Publication	Journal / Conference Name	Advantages	Limitations
Lifelong Federated Reinforcement Learning: A Learning Architecture for Navigation in Cloud Robotic Systems	2019	Robotics & Automation Letters	The shared model was initialized and evolved after training in Env-1. In the cloud robotic system, the robot downloaded the shared model 1G. Then, the robot performed reinforcement learning based on the shared model.	Experiments demonstrate that LFRL is capable of reducing training time without sacrificing accuracy of navigating decision in cloud robotic systems.
Federated Transfer Reinforcement Learning for Autonomous Driving	2022	Springer	As a conclusion, for the autonomous driving areas, with the capabilities of transferring online knowledge from simulators to real-life cars, FTRL-DDPG-SIM performs better than both single execution of single RL agents and federation model with identical RL agents with better training speed and performance.	N/A

Literature Survey (2 papers by Student 2)

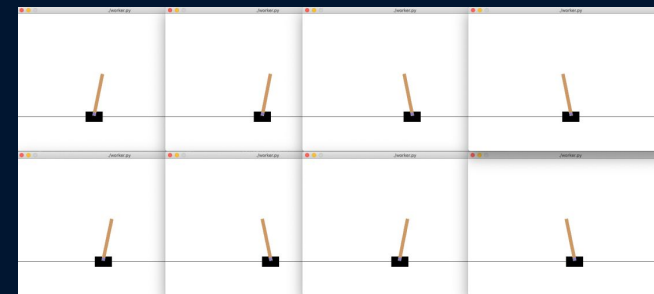
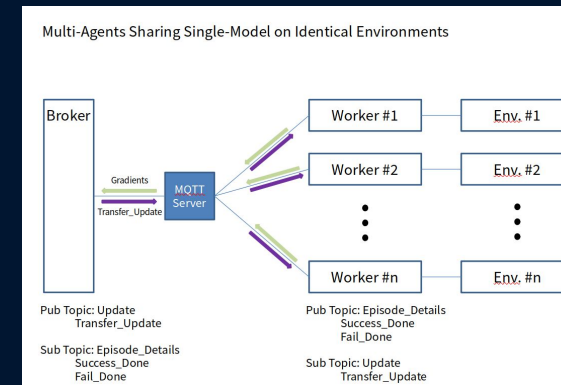
Title of the paper	Year of Publication	Journal/Conference Name	Advantages	Limitations
Federated Reinforcement Learning: Techniques, Applications, and Open Challenges	2021	Harvard Adsabs	Learning experience can be shared among decentralized multiple parties with privacy.	Learning convergence in HFRL
Optimizing Federated Learning on Non-IID Data with Reinforcement Learning	2020	IEEE INFOCOM 2020	Faster convergence speed	N/A

Literature Survey (2 papers by Student 3)

Title of the paper	Year of Publication	Journal / Conference Name	Advantages	Limitations
Federated Reinforcement Learning For Fast Personalization	2019	IEEE AIKE 2019	The table alongside depicts the much higher level of personalization when the number of clients is increased in the same number of iterations or cycles.	Additional overhead and costs associated with implementing
Federated Reinforcement Learning	2019	Cornell University arXiv	Learning experience can be shared among decentralized multiple parties with privacy.	Learning convergence in HFRL

Proposed Approach

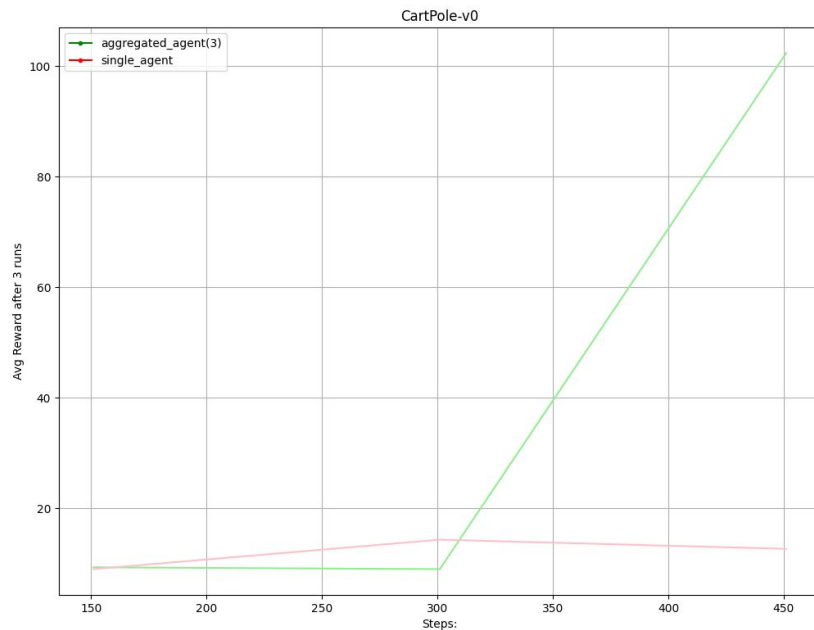
- In order to carry out time optimization to decentralize the federation process with reinforcement learning models implemented on MQTT networks, we've adopted the approach of forming a minimum spanning tree to reduce the Q table transfer times.
- Construction of the graph was done using ping timings for each specific worker node from the broker.
- The weights to generate the same were taken as proportional units to the ping time.
- This network was implemented on top of the usual federation architecture and it is assumed that the reader is aware of the same.
- Reference for federation : <https://deepai.org/publication/federated-reinforcement-learning>



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2  #
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Results and Discussion



- The algorithm developed was tested on the cartpole environment provided by OpenAI Gym.
- On preliminary examination, it was observed that running a single node on the cartpole environment achieved a reward value of 200 after 50 iterations.
- This was in contrast to the federated environment which achieved the same reward value in just two iterations.
- As visualized alongside, federation linearly increases the rate of a constant reward achievement as opposed to a constant value saturation in a single node.

References

(6 Literature Survey Papers web links)

[1] <https://deepai.org/publication/federated-reinforcement-learning>

[2] <https://arxiv.org/abs/2108.11887>

[3] <https://ieeexplore.ieee.org/abstract/document/9155494>

[4] <https://ieeexplore.ieee.org/abstract/document/8791693>

[5] <https://ieeexplore.ieee.org/abstract/document/8772088>

[6] https://link.springer.com/chapter/10.1007/978-3-031-11748-0_15



Thank
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