RateRL: A Framework for Developing RL-Based Rate Adaptation Algorithms in ns-3

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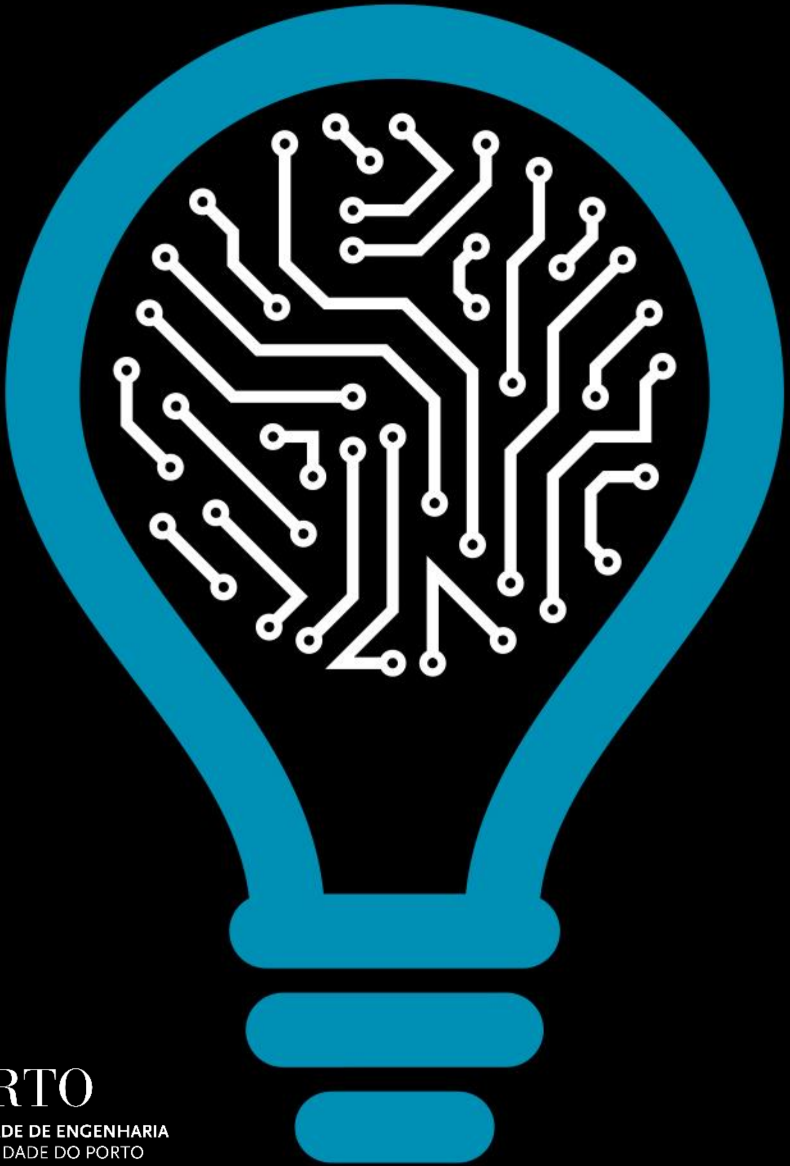

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Presentation Overview

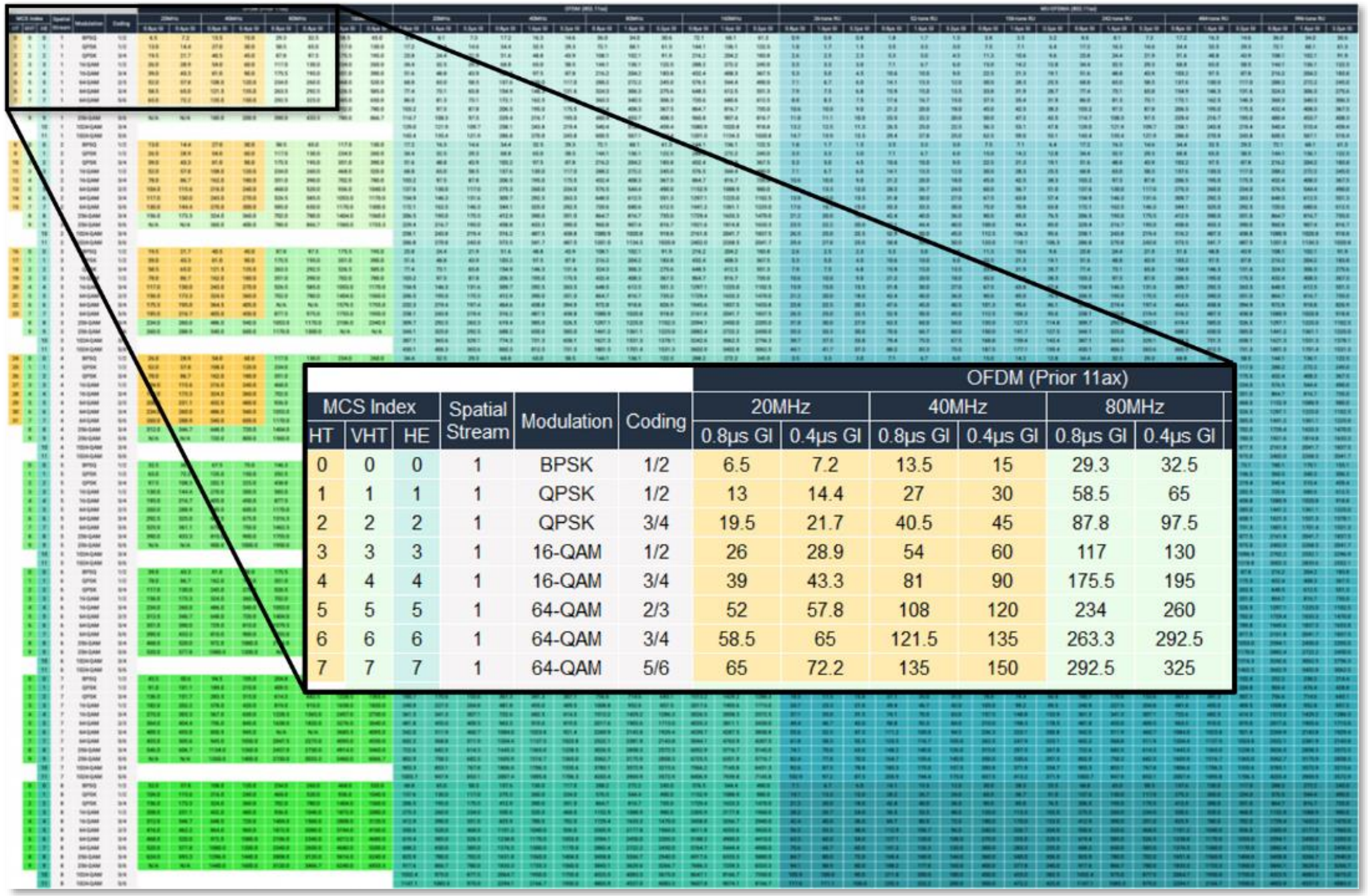
- **Introduction:** Context, Motivation and Contributions
- **Rate** Reinforcement Learning (**RL**) Framework
- **Practical Use Case** of the **RateRL** Framework
- **Conclusions** and Future Work

Introduction

Introduction – Context

- Wi-Fi has introduced new configuration parameters

- **Rate Adaptation (RA)** is becoming **extremely challenging**



MCS Index			Spatial Stream	Modulation	Coding	OFDM (Prior 11ax)					
						20MHz		40MHz		80MHz	
HT	VHT	HE				0.8µs GI	0.4µs GI	0.8µs GI	0.4µs GI	0.8µs GI	0.4µs GI
0	0	0	1	BPSK	1/2	6.5	7.2	13.5	15	29.3	32.5
1	1	1	1	QPSK	1/2	13	14.4	27	30	58.5	65
2	2	2	1	QPSK	3/4	19.5	21.7	40.5	45	87.8	97.5
3	3	3	1	16-QAM	1/2	26	28.9	54	60	117	130
4	4	4	1	16-QAM	3/4	39	43.3	81	90	175.5	195
5	5	5	1	64-QAM	2/3	52	57.8	108	120	234	260
6	6	6	1	64-QAM	3/4	58.5	65	121.5	135	263.3	292.5
7	7	7	1	64-QAM	5/6	65	72.2	135	150	292.5	325

Source: https://mcsindex.com/

Introduction – Motivation

- Most **ns-3** available **RA algorithms** are **obsolete**
  - (AARF, AARFCD, AMRR, APARF, ARF, CARA, **Ideal**, Minstrel, **Minstrel-HT**, Onoe, PARF, RRAA, RRPAA, **ThompsonSampling**)

- Reinforcement Learning (RL) and other Machine Learning techniques are being used to improve the network QoS

- Recent RA algorithms are **ML-based**
  - Insufficient implementation details
  - Source code or training dataset is **usually not available**

This problems emphasize the need for a systematic approach to integrate RL-based RA algorithms into Wireless Networks

Introduction – Contributions

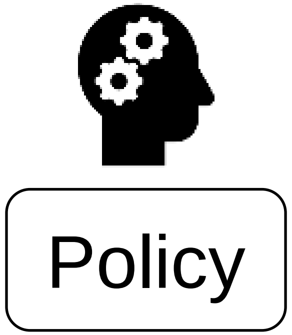
RateRL – A framework to support the development of RL-based RA algorithms

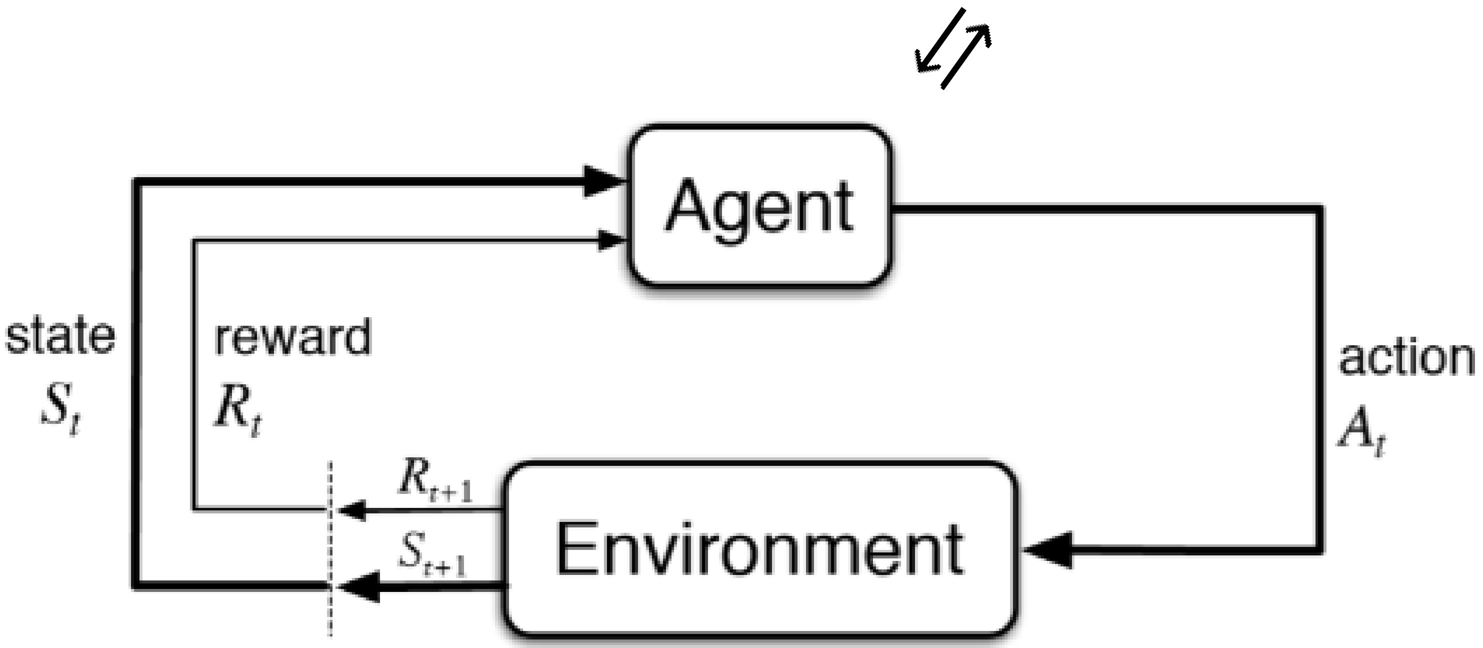
- Pratical use case with a SotA algorithm
- Uses known RL libraries: TF-Agents and OpenAI Gym
- Code and ns-3 scripts are publicly available

RateRL Framework

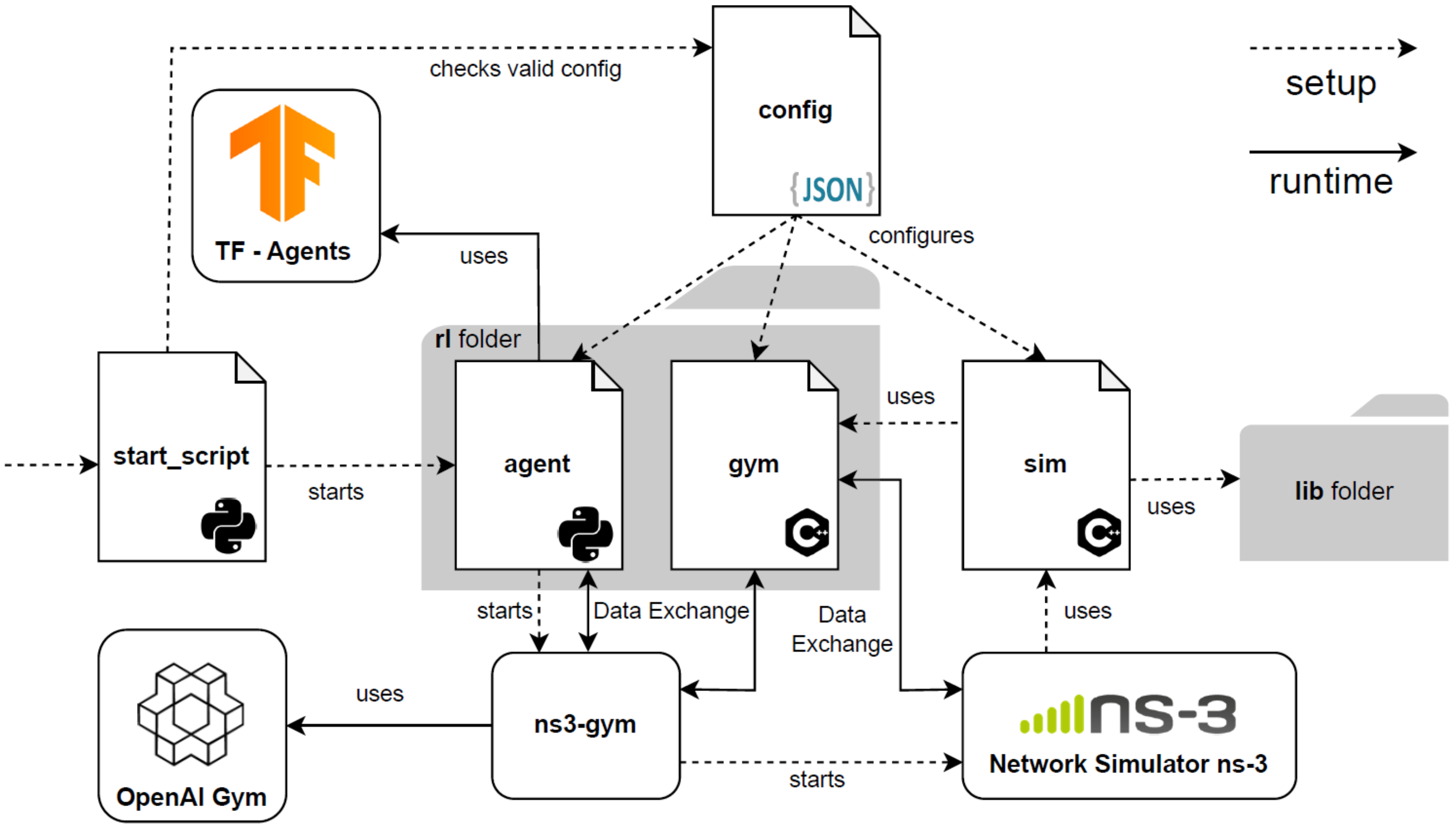
Reinforcement Learning

- **Action → Applied on Environment** to produce a new **State**
- **State** → Defines the state of the **Environment**.
- **Reward** → Evaluates previous **Action/State**.
- **Policy** → Holds the “suggested” **Actions** for every possible **State**





RateRL Architecture



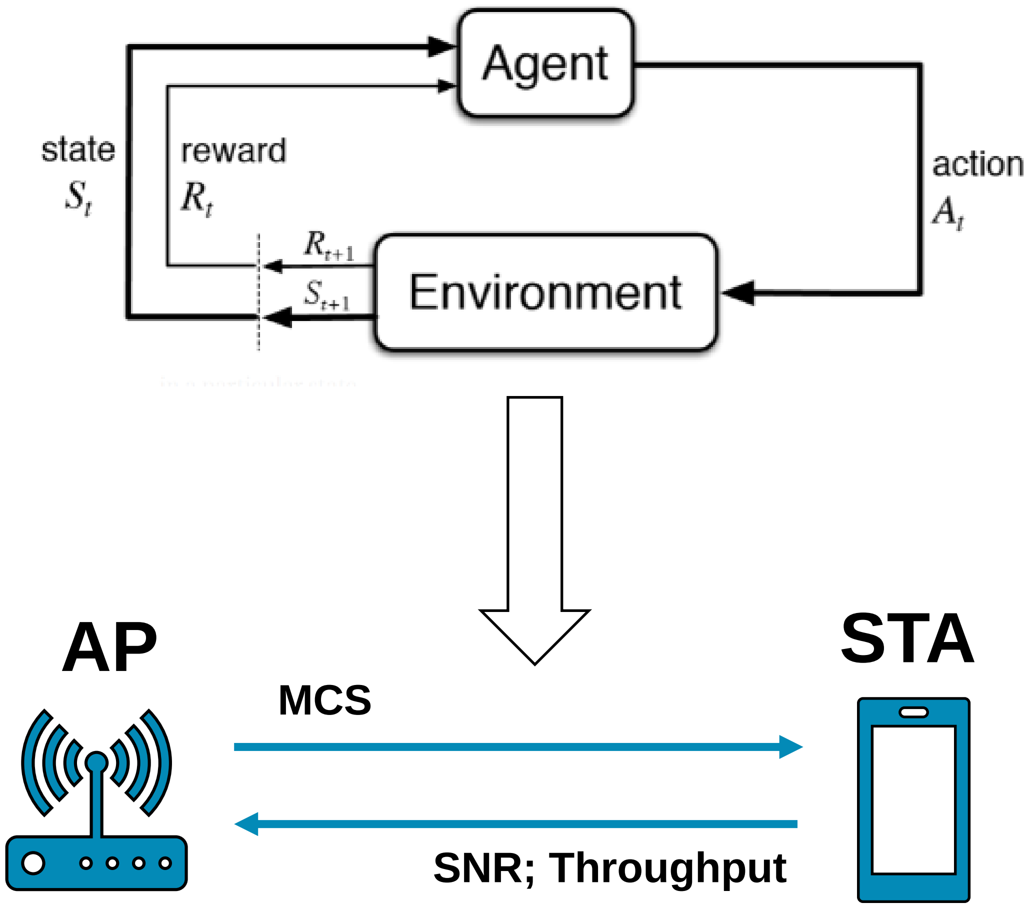
- **Training** – New policy, balancing exploratory and exploiting decisions
- **Evaluation** – Loads a Trained policy to exploit training results

Practical Use Case

Data-driven Algorithm for Rate Adaptation (DARA)[1]

- **Agent** → Framework in **node (AP)**
- **Environment** → Wireless Channel
- **Action** → MCS (0 to 7)
- **State** → SNR (Avg received ACKs)
- **Reward** → Success Ratio and Throughput

$$reward = \frac{MCS_n}{MCS_7} \times FSR, n \in [0,1,\dots,7]$$



[1] Queirós, Rúben, et al. "Wi-Fi Rate Adaptation using a Simple Deep Reinforcement Learning Approach." *2022 IEEE Symposium on Computers and Communications (ISCC)*. IEEE, 2022

Training Scenario and Hyperparameter tuning

- **Training Scenario**
  - 2 Stations, 1 static
  - Other station "walks" away at constant speed to stimulate SNR changes
- **Rationale**
  - Agent observes the whole range of possible states
  - Through trial and error it learns what MCS is best for each SNR intervals
- **Hyperparameter Tuning:**
  - Learning Rate
  - Hidden Layer Architecture

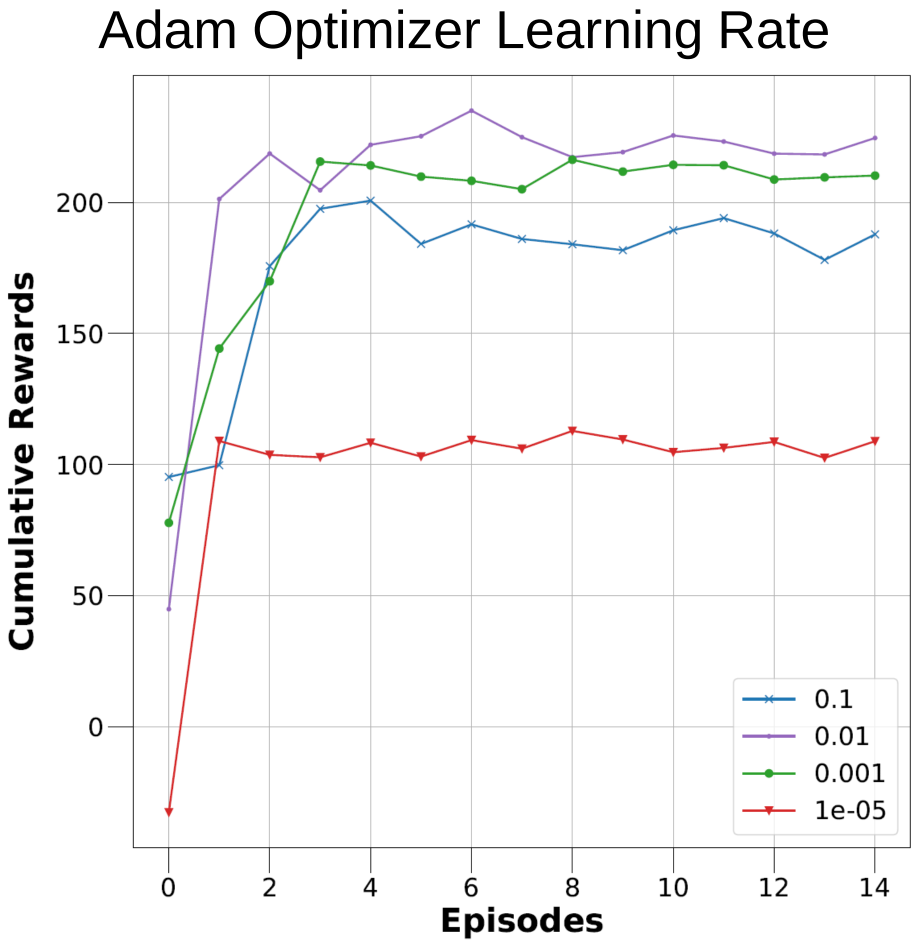
ns-3 simulation configurations

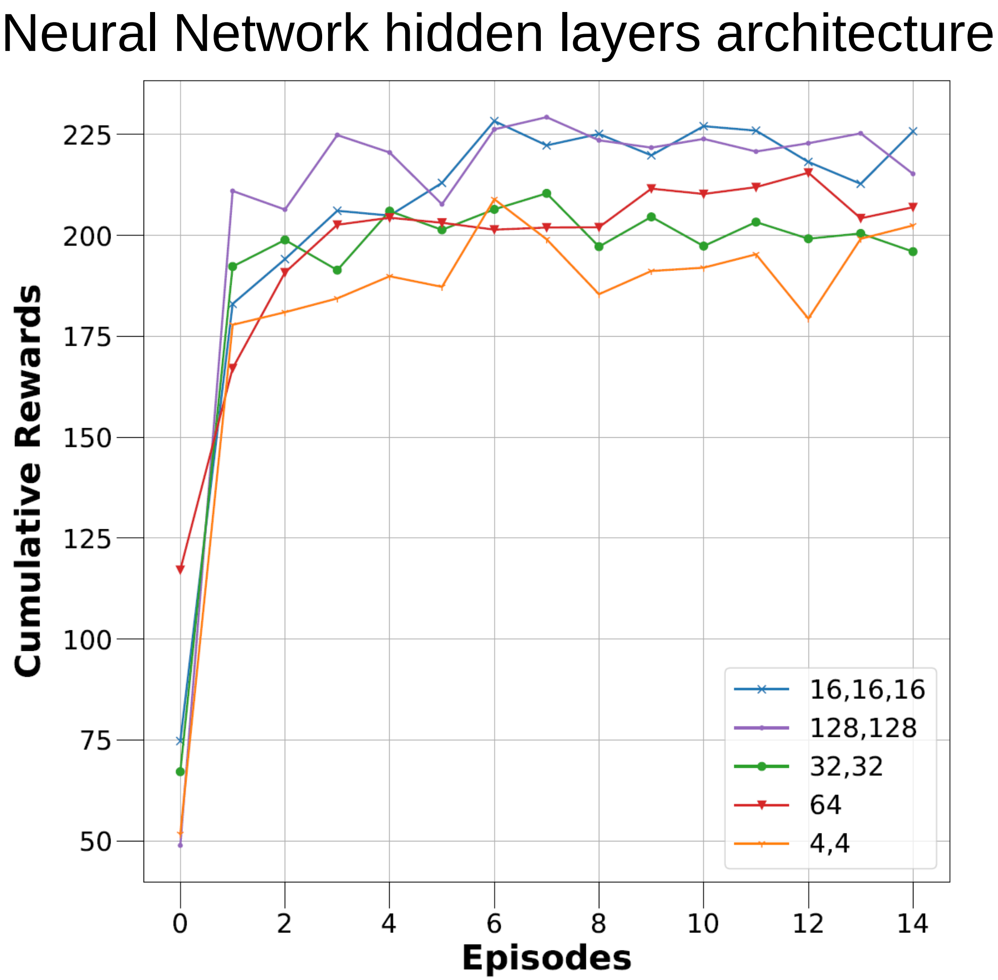
Configuration Parameter	Value
Wi-Fi Standard	IEEE 802.11n
Propagation Delay Model	Constant Speed
Propagation Loss Model	Friis
Frequency	5180 MHz
Channel Bandwidth	20 MHz
Transmission Power	20 dBm
Wi-Fi MAC	Ad-hoc
Traffic	UDP, generated above link capacity
Packet Size	1400 Bytes of UDP Payload

Reinforcement Learning Configurations

Parameter	Value
Observation Space	One-dimensional scaled float (0.0-1.0)
Action Space	One-dimensional integer (0-7)
Optimiser	Adam
Loss Function	Mean Square Error
Epsilon Greedy	Fixed at 0.1
Discount Factor	Fixed at 0.5
Replay buffer	size of 10^6
Batch Size	64

Hyperparameter Tuning Results



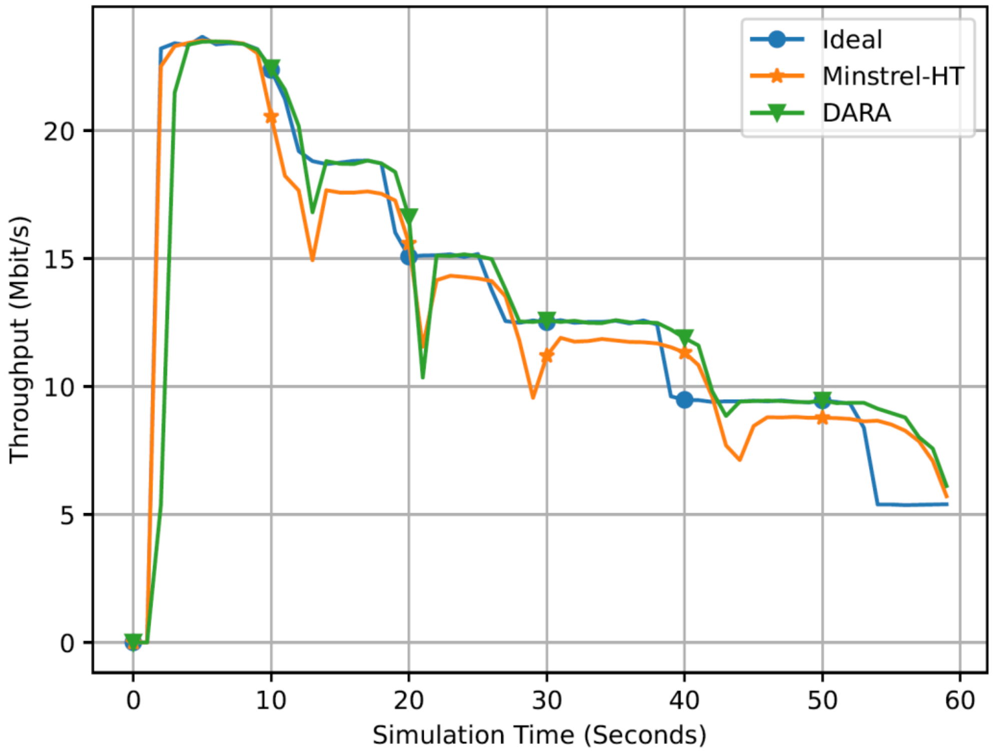


Learning Rate of **0.01** is consistently better than other options

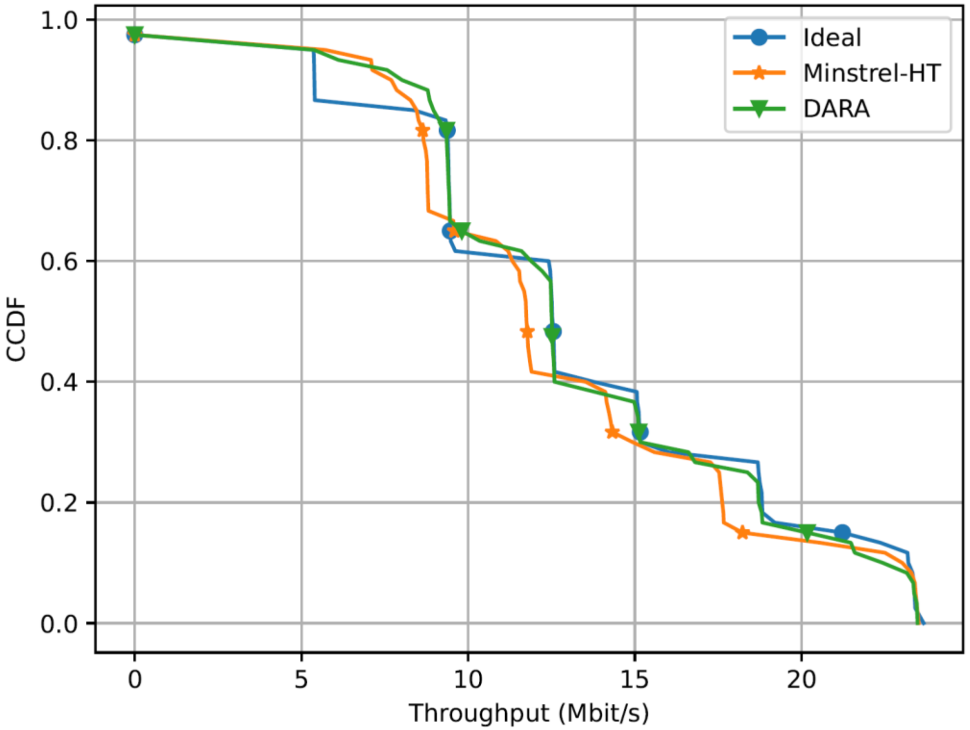
All options with similar performance → **16,16,16** fully connected units

Final Simulation Results

Throughput over simulation episode



Throughput Complementary Cumulative Distribution Function (CCDF)



We successfully implement train and evaluate **DARA** using **RateRL**

Achieving **similar throughput** when compared with **Minstrel-HT** and **Ideal**

Conclusions

Conclusions and Future Work

- We presented **RateRL**, a framework for RL-based Rate Adaptation Algorithms
  - Demonstrated its usage with DARA, a SotA RL-based RA algorithm
  - Framework is open source and publicly available

- **Future Work…**
  - Migrate to ns3-ai to support other popular ML frameworks
  - Extend RateRL to consider other RL Algorithms such as Deep Deterministic Policy Gradient (DDPG) and Proximal Policy Optimization (PPO)

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Thank you!

Questions?

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