Iroko: A Framework to Prototype Reinforcement Learning for Data Center Traffic Control

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Objective:

- Overcome difficulties of Reinforcement Learning to make it useful to learn optimal network policies.
- Design an emulator which allows researchers to deploy different networking topologies and evaluate different congestion control algorithms.

Problem Definition

- Identify difficulties faced by RL algorithms.
- Analyze requirements for Reinforcement Learning to succeed in the datacenter context

Motivation to use RL in networking

- Many data center networking challenges can be formulated as RL problems.
- Some of the problems include: Data-driven flow control, routing and power management.
- RL has the objective of maximizing future rewards.
- RL models have the capability to learn anticipatory policies.
- Current policies are mostly reactive which respond to micro-bursts and flow-collisions.

Difficulties in using Reinforcement Learning

- RL algorithms often suffer from over fitting.
- RL researchers can try out unlimited environmental state representations which can cause RL models to overfit.
- RL algorithms lack reproducibility.
- Reproducibility can be affected by extrinsic factors (e.g. hyperparameters or codebases) and intrinsic factors (e.g. effects of random seeds or environment properties).
- Data center operators expect stable, scalable and predictable behavior.

Requirements of RL

Patterns in Traffic:

- PCC and Remy are two techniques that demonstrate that congestion control algorithms can be evolved from trained data.
- DC traffic pattern can be used to design a proactive algorithm which forecasts traffic matrix and controls host sending rates.

Centralized control algorithms:

- Centralized policy has global view.
- It has ability to plan ahead and grant hosts traffic rates based on the model.

Requirements of RL

Sources of Information:

- CC algorithms use data from transport layer and below.
- It is possible to collect data from network links, switches and other components of hardware.
- Essential to collect congestion signals.
- Some features: switch buffer occupancy, packet drops, port utilization, active flows, and RTT, latency, jitter and queue length.
- Throughput can be used as a metric to optimize.
- One-hot encoding of active TCP/UDP flows per switch port can be used to identify network patterns.

Emulator Design

Key components:

- Network topologies
- Traffic generators
- Monitors
- Agents to enforce congestion policy

Mininet: Software Defined Networking Simulator that can run on single laptop.

RLlib: Library that provides RL abstractions like defining policy, optimizer etc.

Emulator Design

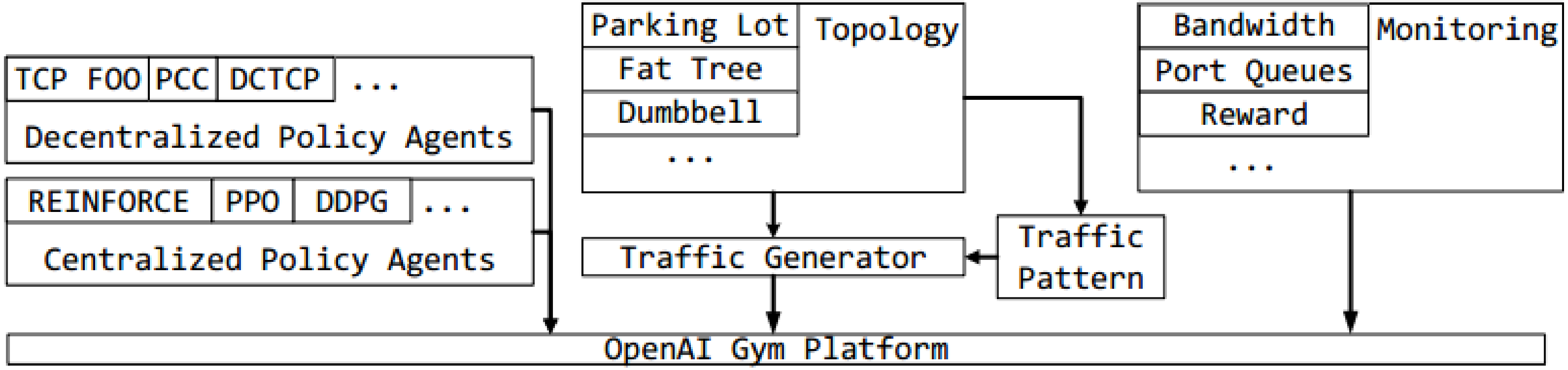


Figure 1: Architecture of the Iroko emulator.

RL implementation in Iroko

Agent action:

- We represent this action set as a vector 'a' of dimensions equal to the number of host interfaces.
- Each dimension a_i represent % of max bandwidth allocated.

$$\mathrm{bw}_i \leftarrow bw_{max} * a_i \quad \forall \quad \mathrm{i} \in \mathrm{hosts}$$

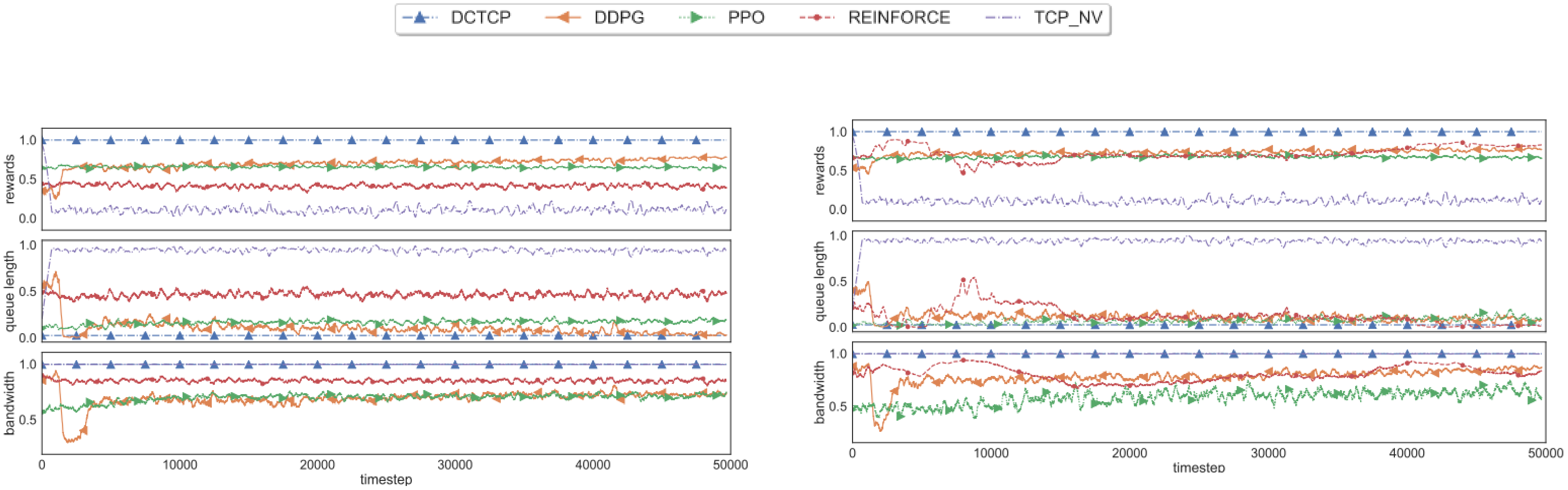
Reward Function:

$$R \leftarrow \sum_{i \in hosts} \underbrace{bw_i / bw_{max}}_{\text{bandwidth reward}} - \underbrace{\text{ifaces}}_{weight} \cdot \underbrace{(q_i / q_{max})^2}_{\text{queue penalty}} - \underbrace{\text{std}}_{devpenalty}$$

Experiments

- Compare the performance of 3 RL algorithms with TCP New Vegas and DCTCP.
- DCTCP: Switches mark packets after the queue length exceeds a threshold.
- TCP New Vegas: Changes the congestion window size based on the RTT observed in packages.
- Rewards for TCP algorithms are also calculated.
- TCP's CC can be confounding with RL's CC

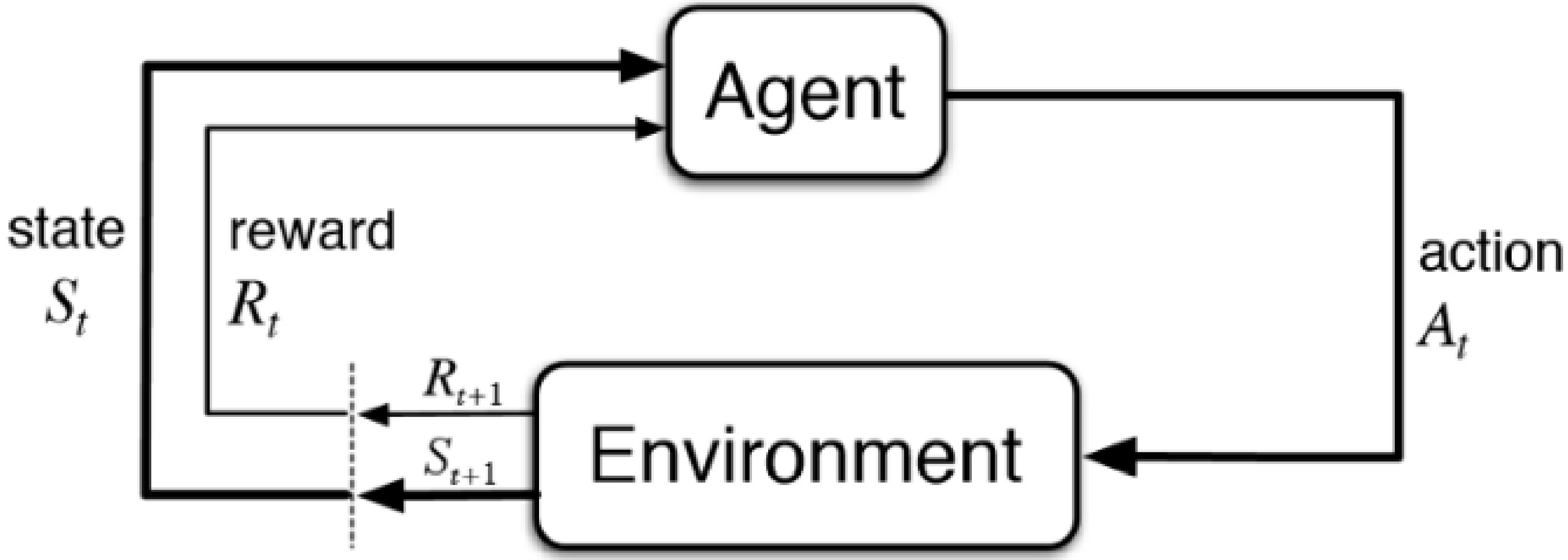
Results


DCTCP
DDPG
PPO
REINFORCE
TCP_NV
rewards
queue length
bandwidth
1.0
0.5
0.0
0
10000
20000
30000
40000
50000
timestep

Conclusion

- Great contribution towards Machine Learning: Interfaced with OpenAI gym
- Carefully analyzed the requirements for RL and tried to provide them in the framework.
- Enables researchers to see the performance of conventional non-RL algorithms through the lens of reward function.
- Not specified the nature of hardware simulated.
- Deals with protocols from TCP/IP stack.

Overview of RL



DDPG Algorithm

Algorithm 1 DDPG algorithm

Randomly initialize critic network $Q(s, a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights θ^Q and θ^μ.
Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q$, $\theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for episode = 1, M **do**
  Initialize a random process $\mathcal{N}$ for action exploration
  Receive initial observation state s_1
  for t = 1, T **do**
    Select action $a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t$ according to the current policy and exploration noise
    Execute action a_t and observe reward r_t and observe new state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in R
    Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from R
    Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
    Update critic by minimizing the loss: $L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$
    Update the actor policy using the sampled policy gradient:

$$\nabla_{\theta^\mu} J \approx \frac{1}{N}\sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)|_{s_i}$$

    Update the target networks:

$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$
$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

  end for
end for

Overview of RL Methods

- https://towardsdatascience.com/introduction-to-various-reinforcement-learning-algorithms-i-q-learning-sarsa-dqn-ddpg-72a5e0cb6287
- https://medium.freecodecamp.org/an-introduction-to-reinforcement-learning-4339519de419

- PPO: Standard policy gradient methods perform one gradient update per data sample, we propose a novel objective function that enables multiple epochs of minibatch updates.
- Reinforce: Weight adjustments in direction of gradients of immediate reinforcement and delayed reinforcement.