Constrained Policy Optimization for Load Balancing

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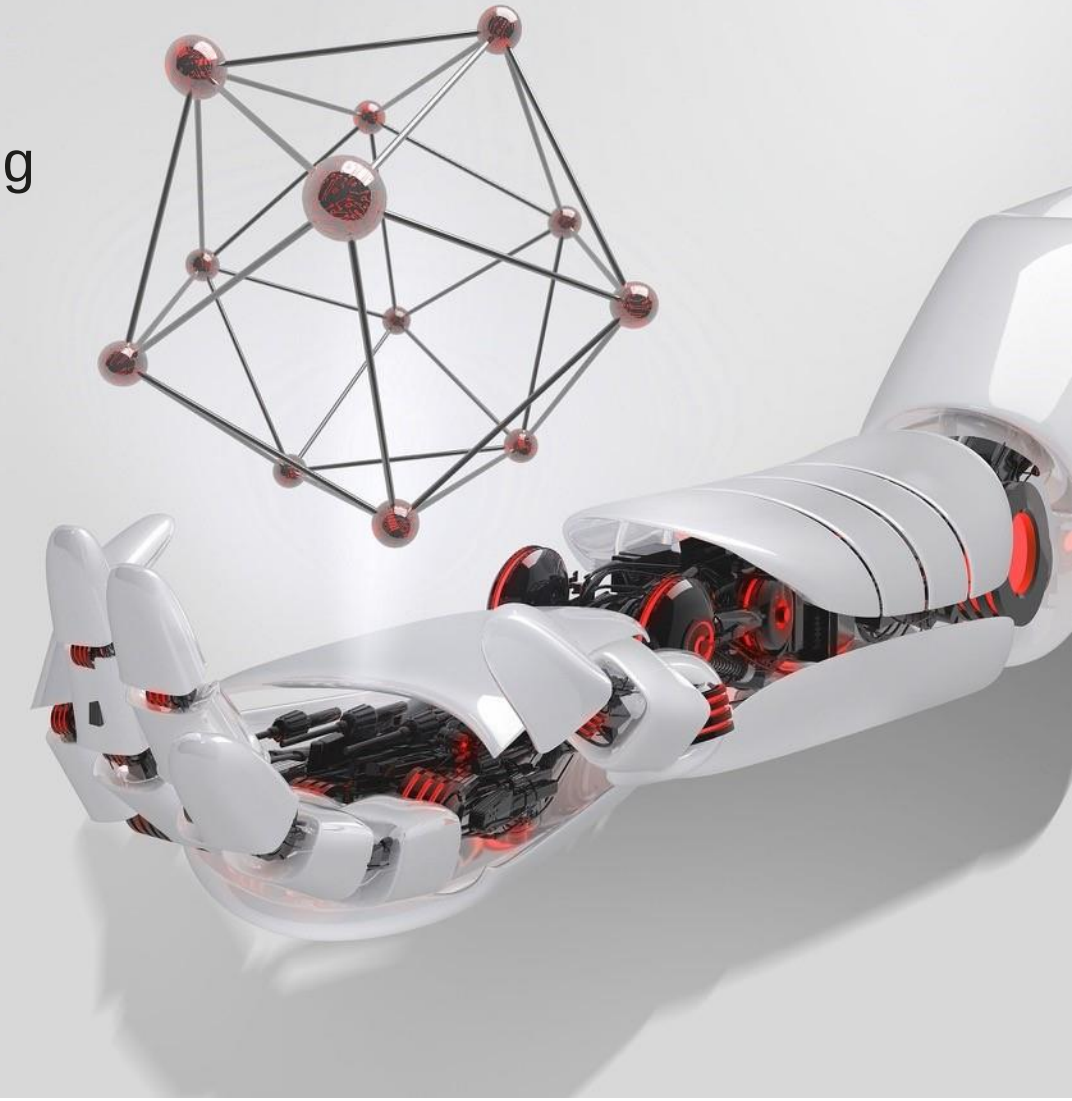
AlgoTel 2021, La Rochelle



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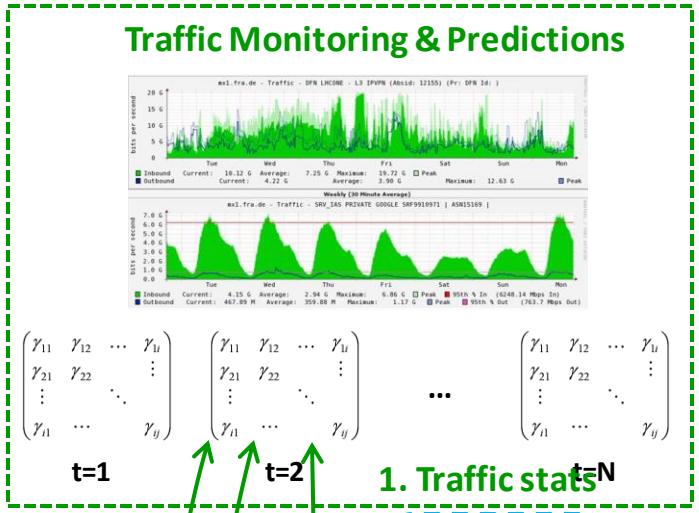
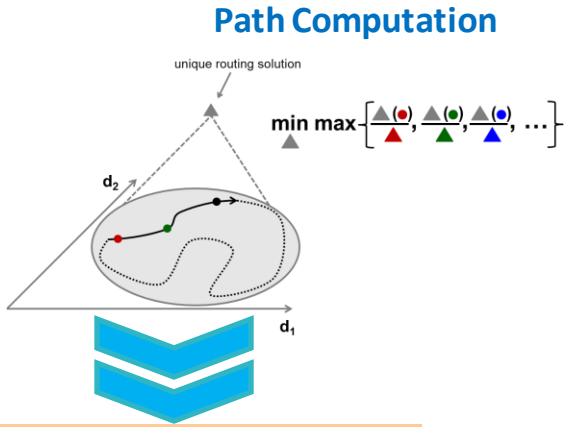
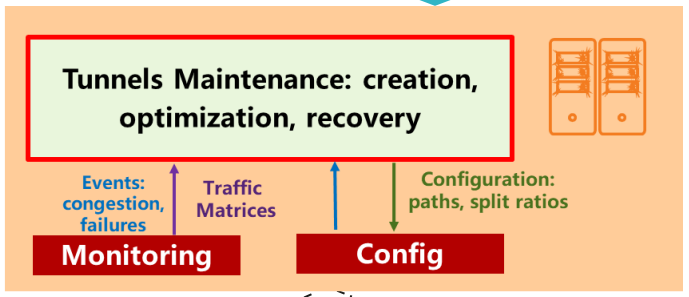
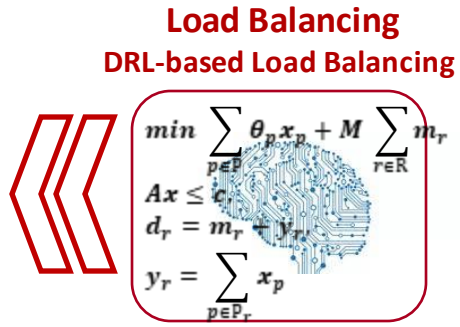
Centralized TE architecture

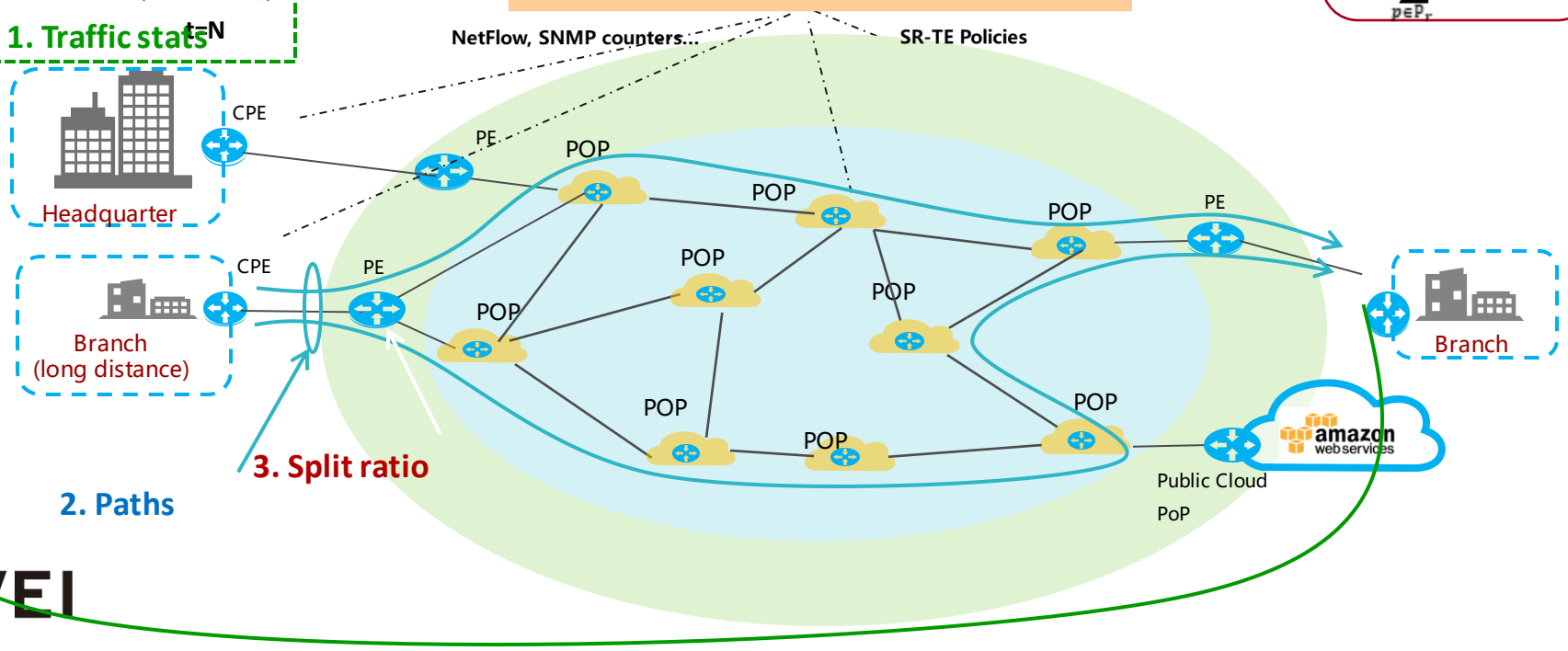
Slow and Fast Control Loops







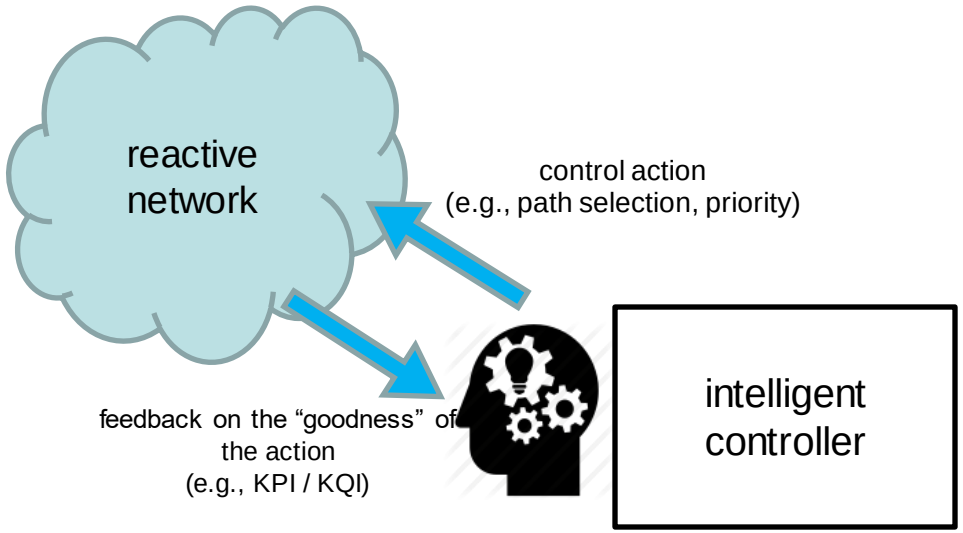




Load Balancing: A good use case for RL

Reinforcement Learning is ideal for non-explicit model

- Traffic patterns are difficult to characterize
- The impact of routing decisions on KPIs (delay, jitter, packet loss) is difficult to anticipate
- The impact of routing decisions on KQI (e.g., QoE) is difficult to anticipate

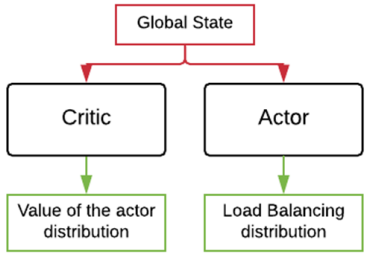


Load Balancing: A good use case for RL

RILNET

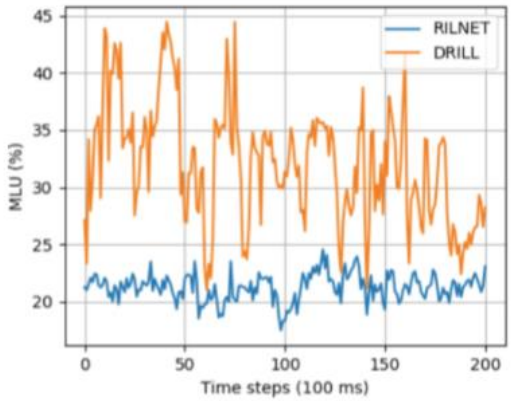
RILNET: A Reinforcement Learning Based Load Balancing Approach for Datacenter Networks. MLN 2018.

- Centralized Actor / Critic approach
- Offline training based on an abstract model (training speedup)
- Fixed policy
- State of art algorithm : DDPG (Deep Deterministic Policy Gradients)

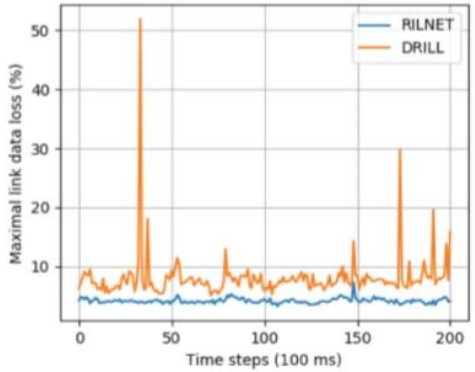


Results

- Compared to DRILL in DCN
  - Improvement of the MLU by 30% and link delay / latency by 40%



(a) MLU



(c) Maximal link data loss

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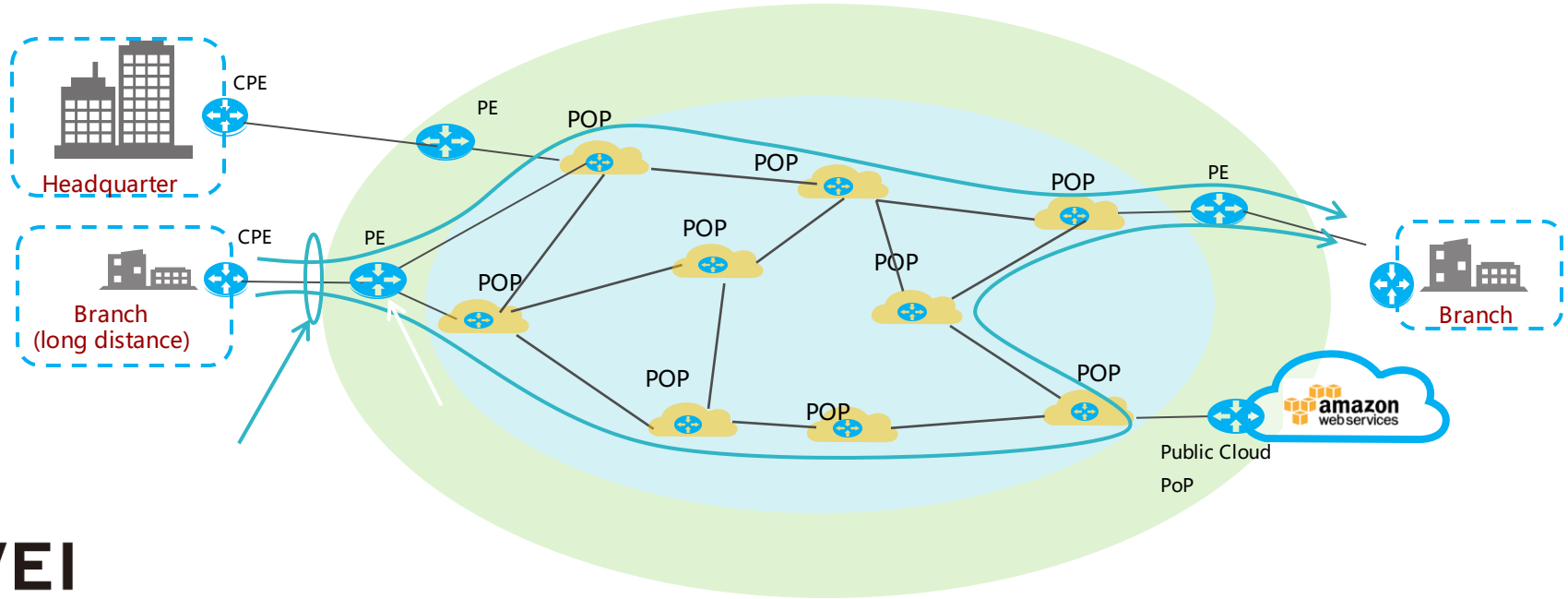
Outline

- Centralized TE
- Load balancing model
- Constrained MDP & RCPO
- Simulation results
- Conclusions

Load balancing problem

Time-based slot
Pre-defined paths
Only split ratio are changed
Minimize delay without too much drops



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MM1 delay model

Markovian arrival process:

Packet arrivals occur at rate λ according to Poisson process

Markovian service process:

Service times have exponential distribution μ

1 server

Packet size

Propagation delay

$$\frac{S}{C_e - \sum_k d^k(t) \sum_{\substack{p \in P^k \\ e \in p}} x_p^k\ (t)} + \lambda_e$$

Capacity (bps)

Load (bps)

http://www.pitt.edu/~dtipper/2120/mm1_tutorial.pdf

NLP-based approach

Delay variable for tunnels

$$\min \sum_{k \in K} d_k$$

Linking constraints

$$D_k y_{pk} \geq x_{pk} \qquad \forall k \in K, p \in \mathbb{P}_k$$

$$D_k x_{pk} \geq y_{pk} \qquad \forall k \in K, p \in \mathbb{P}_k$$

Delay variable of edges

MM1 constraints

$$z_e \geq \frac{1}{c_e - \sum_{k \in K} \sum_{p \in \mathbb{P}_k : e \in p} x_{pk}} \qquad \forall e \in E$$

Capacity constraints

$$\sum_{k \in K} \sum_{p \in \mathbb{P}_k : e \in p} x_{pk} \leq c_e, \qquad \forall e \in E$$

Ratio variable for tunnels

Delay constraints

$$\sum_{e \in p} z_e y_{pk} \leq d_k \qquad \forall k \in K, p \in \mathbb{P}_k$$

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LearnQueue [Bouacida19]

Proposed for wireless network
Two-part reward (delay and loss)
Manual configuration for priority

Learn Queue reward $r_t = r_d^t + r_{enq}^t$
Delay related part: $r_d^t = -\delta \sum_k d_k(t)$
Loss related part: $r_{enq}^t = (1-\delta) er^t$

[Bouacida19] N. Bouacida and B. Shihada, "Practical and Dynamic Buffer Sizing Using LearnQueue," in IEEE Transactions on Mobile Computing, vol. 18, no. 8, pp. 1885-1897, 1 Aug. 2019

Constrained MDP & Reward Constrained Policy Optimisation

State $s \in \mathbb{S}$
Action $a \in \mathbb{A}$
Transition model P(s' | s, a): probability of going to s' from s depends only on s and action a
Reward $r(s_t, a_t)$
Penalty $c(s_t, a_t)$
μ: initial state distribution
Constraint $C(s_t) = F(c(s_t, a_t), \ldots, c(s_N, a_N))$, e.g.
F: discounted sum or average

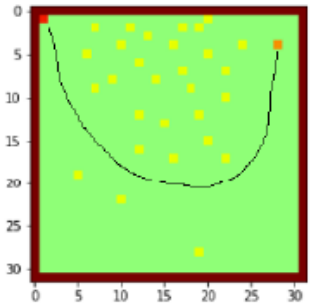
$$\max_{\pi \in \Pi} J_R^\pi$$

s.t. $J_C^\pi \leq \alpha$

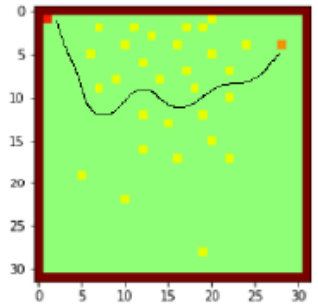
$\alpha \in [0,1]$

$$J_R^\pi = \mathbb{E}_{s_0 \sim \mu}^\pi \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right]$$

$$J_C^\pi = \mathbb{E}_{s_{0 \sim \mu}}^\pi [C(s)]$$



(a) $\alpha = 0.01$



(b) $\alpha = 0.5$

Lagrangian relaxation

$$\min_{\lambda \geq 0} \max_{\theta} L(\lambda, \theta) = \left[J_R^{\pi_\theta} - \lambda \left(J_C^{\pi_\theta} - \alpha \right) \right]$$

$$\hat{r}(\lambda, s, a) \triangleq r(s, a) - \lambda c(s, a)$$

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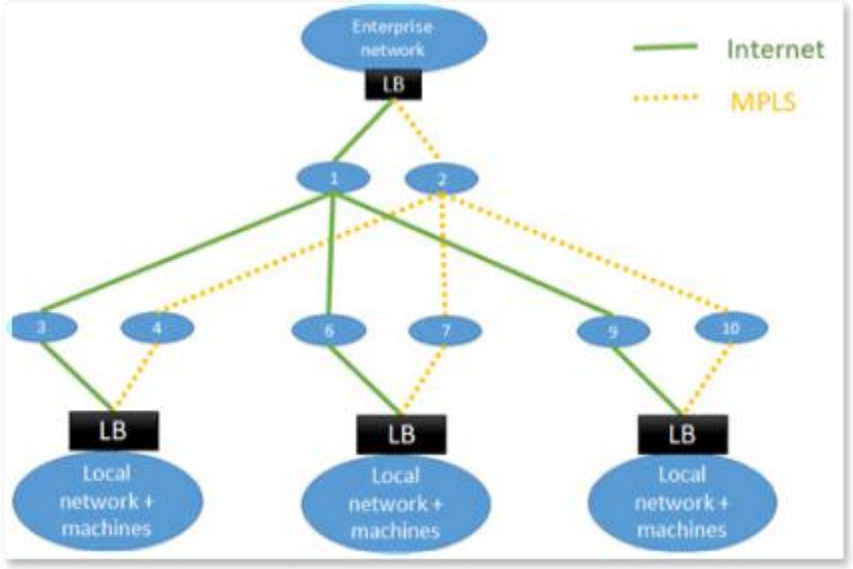
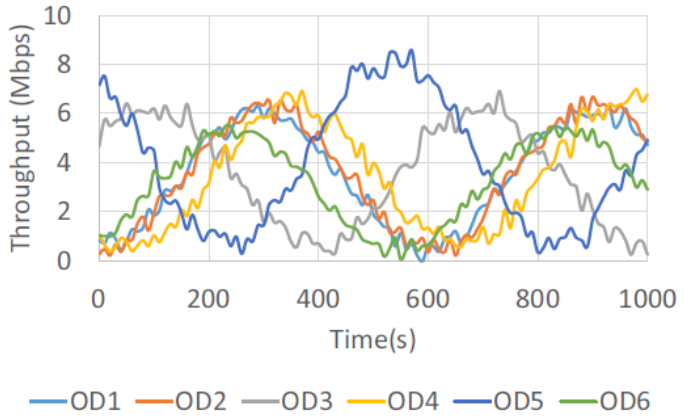
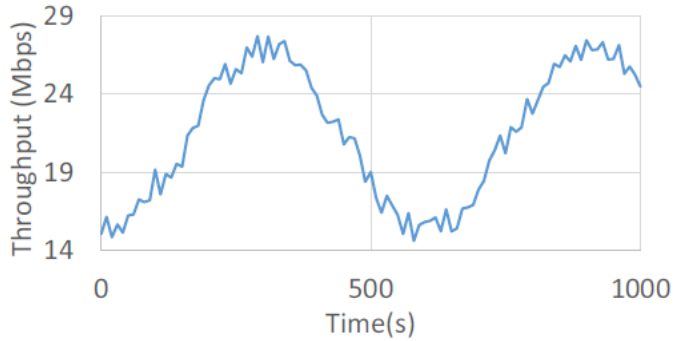
Simulation scenario

SD-WAN toy scenario







Algorithms			
DDPG-LearnQueue 0.1	DDPG-LearnQueue 0.9	RCPO	Model-based approach
LearnQueue reward with $\delta = 0.1$ (Prefer Traffic Admission)	LearnQueue reward with $\delta = 0.9$ (Prefer low delay)	Penalized reward function	Delay
Stable baseline		Stable baseline + modifications	SCIP
2 hidden layers (128 neurons each) ReLU $\gamma = 0.7$		Similar to DDPG-LQ $\eta_1 = 0.01$	Max time=60s

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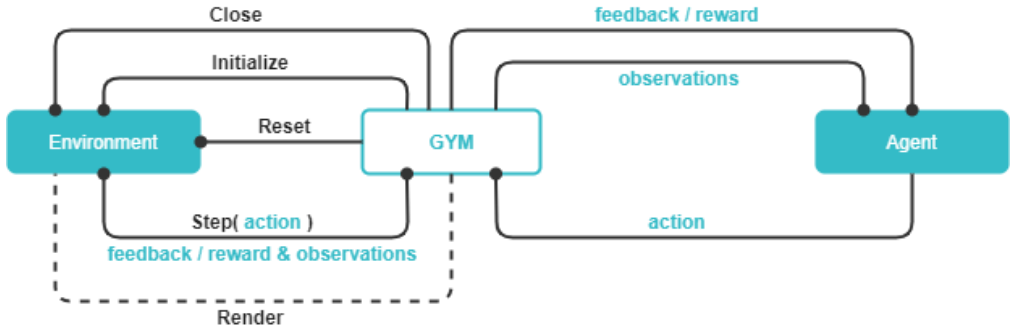
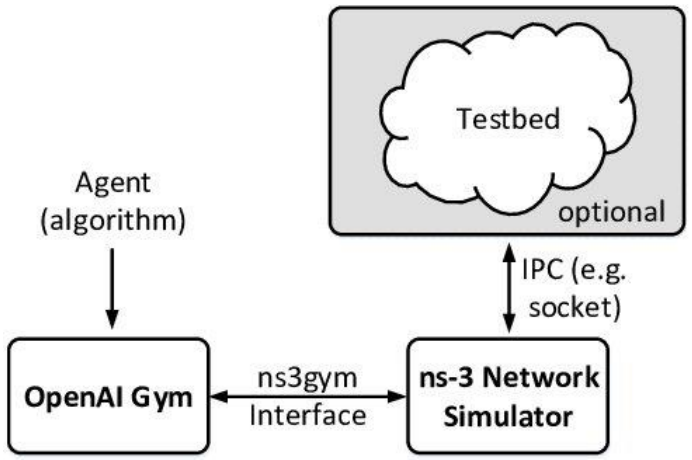
OpenAI Gym environment

"Simplified environment" with M/M/1 model



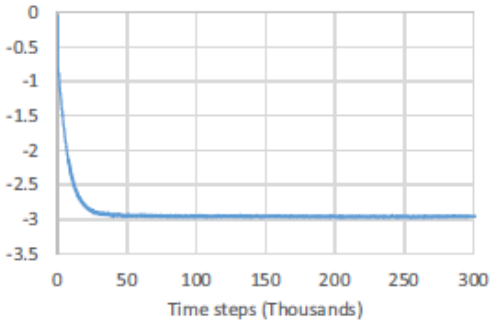
Possible to extend to a packet-level simulator (i.e., ns3) [Gawłowicz18]



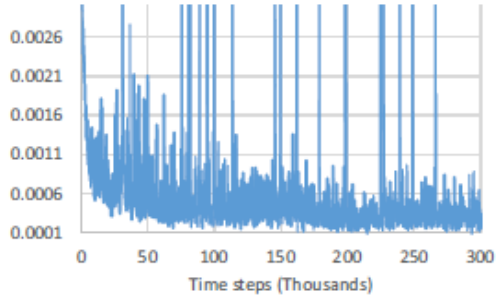
[Gawłowicz18] Gawłowicz, Piotr, and Anatolij Zubow. "ns3-gym: Extending openai gym for networking research." *arXiv preprint arXiv:1810.03943* (2018).

Convergence

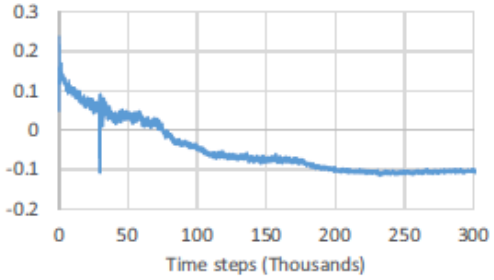
LearnQueue



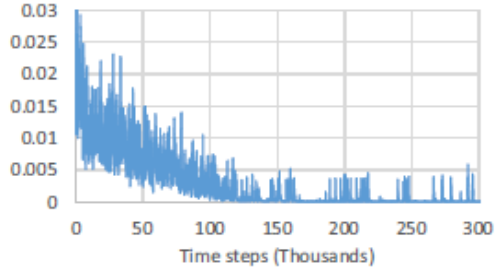
(a) Actor, $\delta = 0.1$



(b) Critic, $\delta = 0.1$

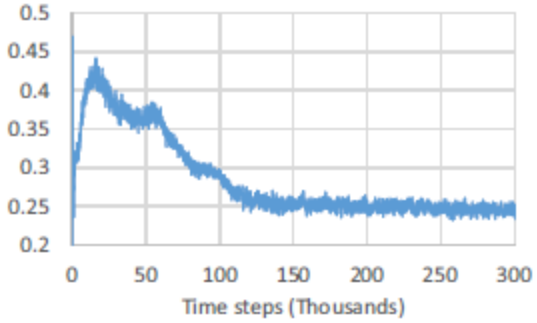


(c) Actor, $\delta = 0.9$

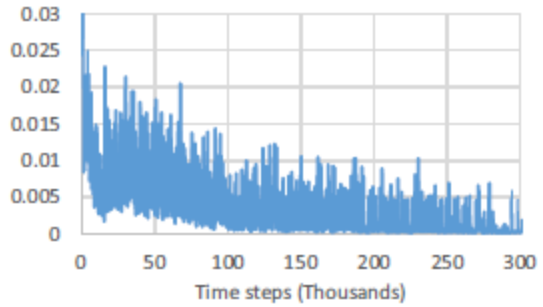


(d) Critic, $\delta = 0.9$

RCPO



(a) Actor loss



(b) Critic loss

Convergence after 100k time steps

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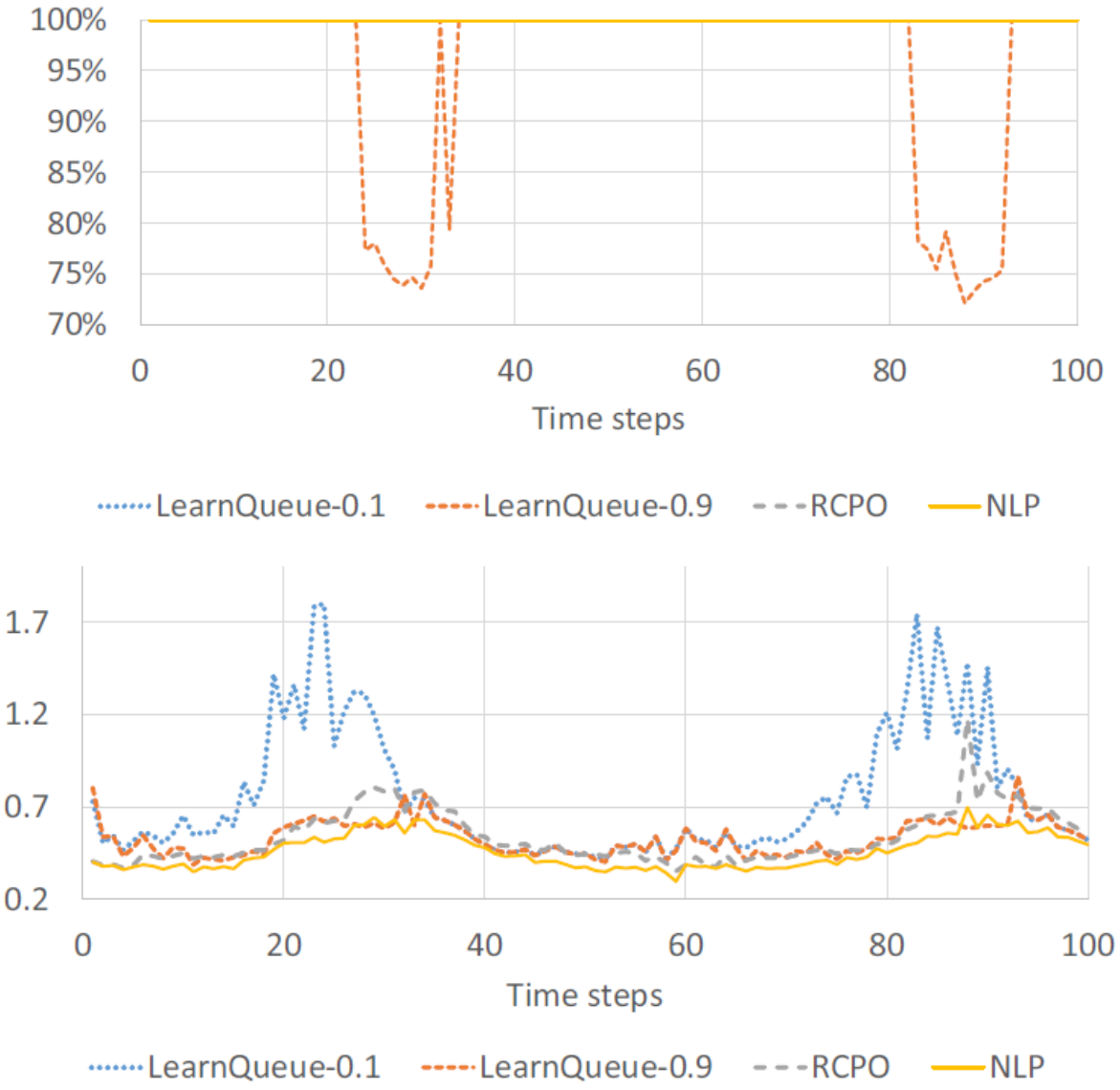
Simulation results



LearnQueue:

- Prefer delay ($\delta = 0.9$) : RL agent will reject traffic when congestion happens
- Prefer traffic admission ($\delta = 0.1$): RL agent will admit 100% traffic even it increases the delay

RCPO: well balanced between traffic admission and good delay (comparable with NLP)

Conclusions & Perspective

- RCPO minimize constraint violations
- Comparable to optimal solution

- Packet-level simulation
- Comparison with Control Barrier Function

Thank you for
your attention