Towards In-Switch Reinforcement Learning

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Data-driven networking: RL in networks

Data-driven networking: Automate control, optimisation, configuration of the network.

- Flow performance optimisation.
- · Resource allocation.
- · Adaptive response to load, intrusions, etc.
- Feedback loop-like.

Why programmable data-planes?

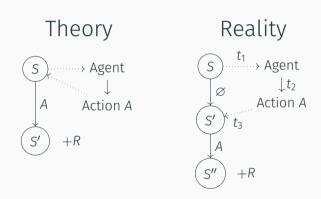


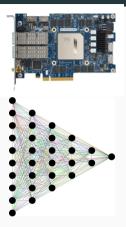
Figure 1: Asynchronous RL delays and state slippage (policy updates omitted).

- In data-driven, want to minimise time to act.
- RL assumes that action & policy update are zero-cost.
 - Not so in real deployments!
 - State drift, etc.
- Controller contact time, serialisation, ...
- In other ML, often need line rate inference.
- Programmable network hardware fills this niche

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Recent Programmable Trends in Data-Driven Networks

- ML acceleration, line-rate packet classification.
- How? Train model off-NIC, convert to binary neural network¹, or decision tree².
- Limits? No online training, cost of backprop algo (expensive!), vast data needs.
- · What if we need online learning?



¹Siracusano et al., 'Running Neural Networks on the NIC'.

²Xiong and Zilberman, 'Do Switches Dream of Machine Learning?: Toward In-Network Classification'.

Case study: DDoS Prevention



Figure 2: 'Global' state for any flow (bold means used by policy).

- Prior work³.
- Monitor flow statistics at ingress/egress points.
- Use load measurements from flow paths as global state.
- OUTPUT: throttle individual flows.
- Classical RL.
 - Learning time on order of minutes.

³Simpson, Rogers and Pezaros, 'Per-Host DDoS Mitigation by Direct-Control Reinforcement Learning'.

Case Study: DDoS Prevention (Architecture)

- Reward measurements come from network.
- Input state mixes local flow data with global load data.
- Flow measurements combined, decisions scheduled to prevent overload.

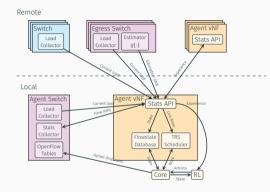


Figure 3: (Non-PDP) system architecture for RL-driven DDoS defence.

Goal	Solution	Drawback
On-NIC action compute		
 On-NIC learning 		
 Direct action installation 		
 (Partly) External State, Rewards, 		
and Task Independence		
Runtime reconfiguration		

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On-NIC learning	Classical RL	Info capacity
 Direct action installation 	Custom actions	No intrinsic support
• (Partly) External State, Rewards,	Independent Module	_
and Task Independence		
 Runtime reconfiguration 	P4 Parser + RTE	_

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We'll mainly focus on SmartNICs.

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Architecting On-NIC RL

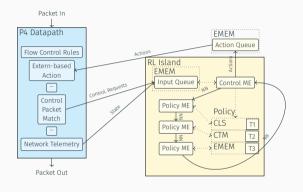


Figure 4: Architecture for generalised RL agent on Netronome hardware.

- Classical RL built on tile-coding—online.
- · Async wrt. datapath.
- Dynamic selection of last reward, trace info.
- Runtime configurable (policy, size, application) from data/control-plane.
- Task independent.

How could this (hypothetically) fit the case study?

- P4 table-action to gather state on collected flows.
 - · Flow telemetry in P4 well-documented.
 - Pass in/schedule state vectors every δt .
- Directly pass reward measurements to RL core.
- · Base policy installed by controller, updated live.
- Matched packets poll actions from RL core.
 - Map RL actions to state machine, maintain throttling hash table.
 - Every $\delta t'$, batch actions to controller.

Timing: Why not offload to the controller?

For SmartNICs, the attached host is the (closest) controller.

- PCIe access times $\mathcal{O}(\mu s)$.⁴
- MATs recompiled $\mathcal{O}(s)$. Many rules \implies batching.
- Thrift serde time $\mathcal{O}(ms)$.

Meanwhile core-to-core on chip around 100 ns @ 1.2 GHz.

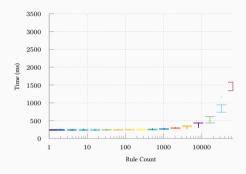


Figure 5: Netronome rule installation cost (1 table, 1–65 536 rules).

⁴Neugebauer et al., 'Understanding PCIe performance for end host networking'.

Quantisation

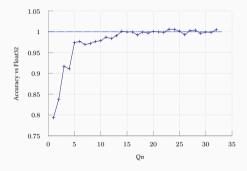


Figure 6: DDoS throttle accuracy wrt. fixed-point Qn.

No FPU... so use Qn fixed-point.

- For RL updates: need only shift, multiply, add.
- Policy exec only needs add.
- 16 bit fraction has negligible loss.

Dynamic Action Installation

- Netronome w/ P4?
 - MAT structure (DCFL) computed on host...
 - · So can't directly interop with P4.
 - · ...But we can have other actions/externs maintain their own lookup tables.
- · Tofino has features to make this more feasible.
 - Action Profiles/Selects

Execution costs (Q15.16)

- Single-threaded—still to be accelerated.
- Small? One tiling per memory tier.
- Max? 20-element state, 17 mixed-dim tilings, 8 per set.
- Versus use-case: 330 μs on commodity i7 (4.2 GHz).

Policy Size	Action (μs)	Plus Update (μs)
Small	10.66	14.60
Max (DDoS)	512.67	612.55

Takeaways:

Online in-NIC RL is possible!

In-switch? Less so.

Platform-specific, but similar design for SmartNIC hardware class.

Work-in-progress: end-to-end timing, training accuracy, other use-cases (AQM?), optimisation.

Questions?