Revisiting the Classics: Online RL in the Programmable Dataplane

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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?

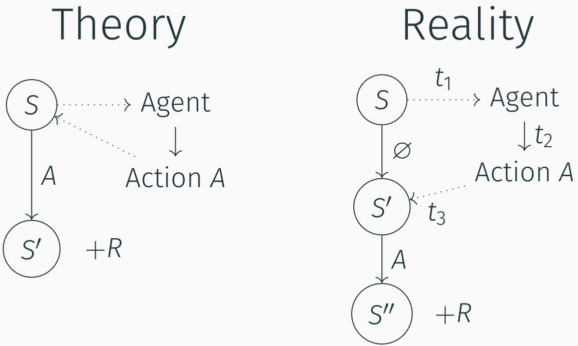
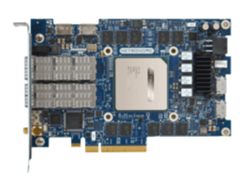


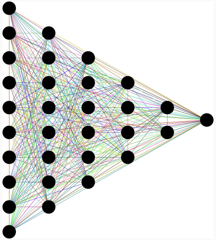
Figure 1: *Asynchronous RL delays and state slippage (policy updates omitted).*

- 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.

Recent Programmable Trends in Data-Driven Networks

- ML acceleration, line-rate packet classification.
- How? Train model off-NIC, convert to binary neural network[1], or decision tree[2].
- Limits? No online training, cost of backprop algo (expensive!), vast data needs.
- What if we need online learning?





[1] Siracusano *et al.*, ‘Running Neural Networks on the NIC’.
[2] Xiong and Zilberman, ‘Do Switches Dream of Machine Learning?: Toward In-Network Classification’.

Timing: Why not offload to the controller?

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

- PCIe access times $\mathcal{O}(\mu s)$[3]
- Crossing VMs/vNFS has $\sim 10\times$ higher cost[4]
- MATs recompiled $\mathcal{O}(s)$. Many rules $\implies$ batching.

Meanwhile core-to-core on NFP around 140 ns @ 1.2 GHz.

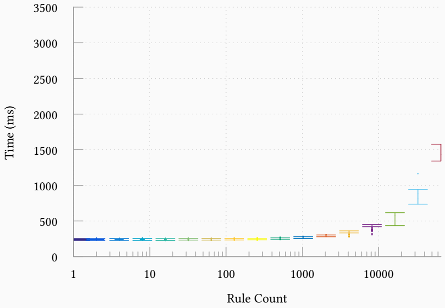
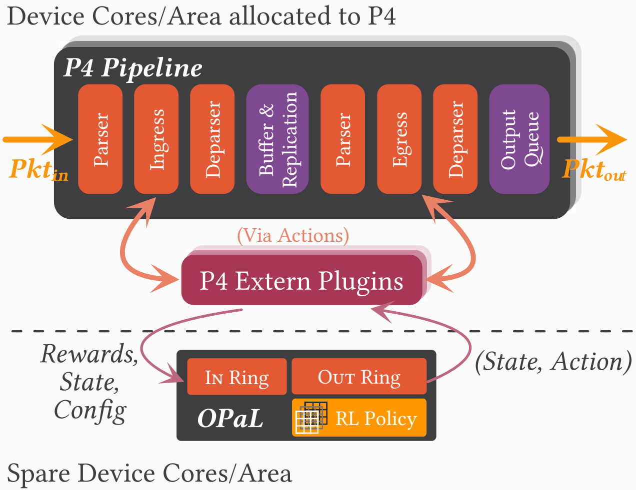


Figure 2: *Netronome rule installation cost (1 table, 1–65 536 rules).*

[3] Neugebauer *et al.*, 'Understanding PCIe performance for end host networking'.
[4] Cziva and Pezaros, 'Container Network Functions: Bringing NFV to the Network Edge'.

How do we bring online, in-NIC RL?



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

Background and Design

Single-step (classical) RL—Sarsa

A simple explanation:

How to select an action? Pick largest from list: $\hat{\mathsf{q}}(S_t, \cdot, \mathbf{w}_t)$

How should we adjust the value of selected items?

$$\delta_t = \overbrace{R_{t+1} + \gamma\, \hat{\mathsf{q}}(S_{t+1}, A_{t+1}, \mathbf{w}_t)}^{\substack{\text{New target value:}\\ \text{Reward+some of the next action's value}}} - \underbrace{\hat{\mathsf{q}}(S_t, A_t, \mathbf{w}_t)}_{\text{Current value estimate}},$$

Policy parameter update:

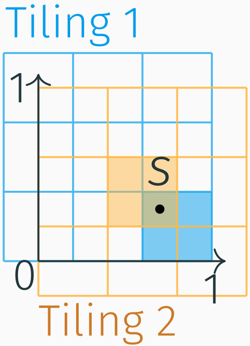
$$\mathbf{w}_{t+1} = \mathbf{w}_t + \overbrace{\alpha\delta_t}^{\text{Move a little bit of } \delta_t \text{ along...}} \underbrace{\nabla\hat{\mathsf{q}}(S_t, A_t, \mathbf{w}_t)}_{\text{...the policy's gradient}}.$$

Design implications?

Tile Coding

$$s = \begin{pmatrix} 0.7 \\ 0.3 \end{pmatrix}$$

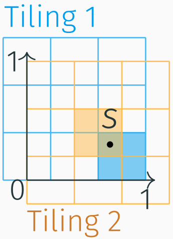
$$\mathbf{x}(s, \cdot) = \begin{Bmatrix} T_{1,9}, \\ T_{2,5}, \\ T_{bias} \end{Bmatrix}$$



Tile Coding (ii)

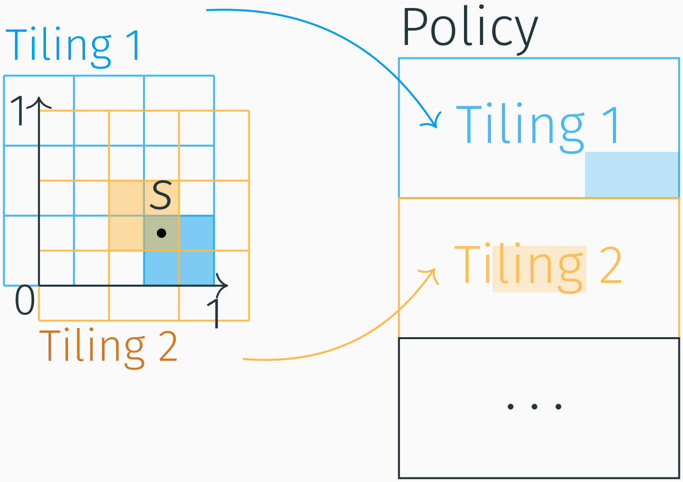
$$s = \begin{pmatrix} 0.7 \\ 0.3 \end{pmatrix}$$

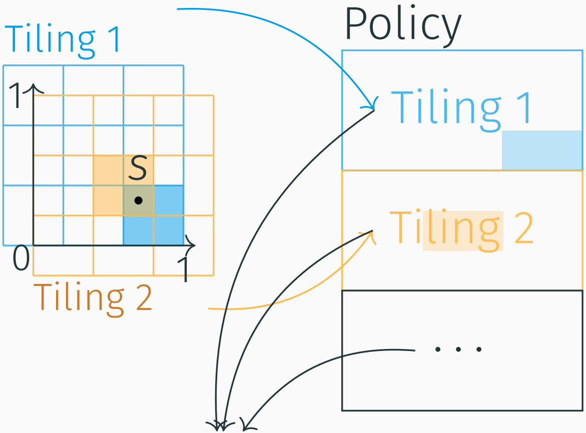
$$\mathbf{x}(s, \cdot) = \begin{Bmatrix} T_{1,9}, \\ T_{2,5}, \\ T_{bias} \end{Bmatrix}$$



- Operations? $+, -, \times, \div$
  - PoT tile width? $\div$ replaced w/ shift.
- Tiling set: identical dimensions, different shifts
- Gradient for RL?
  - List of hit tiles.
- Can be more complex...

Tile Coding: Parallelism



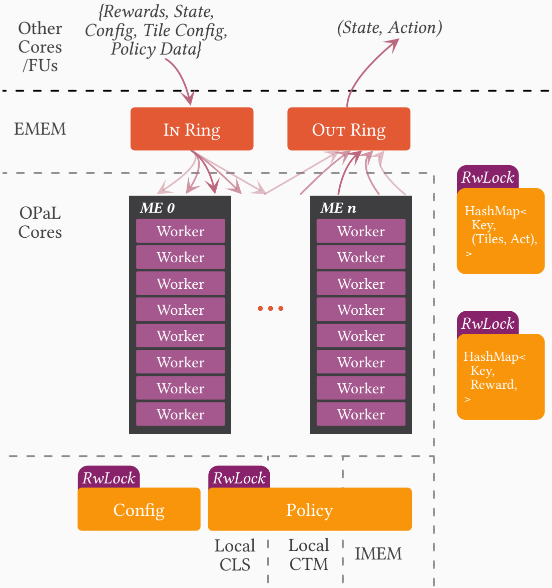


$$a = [\cdots]$$

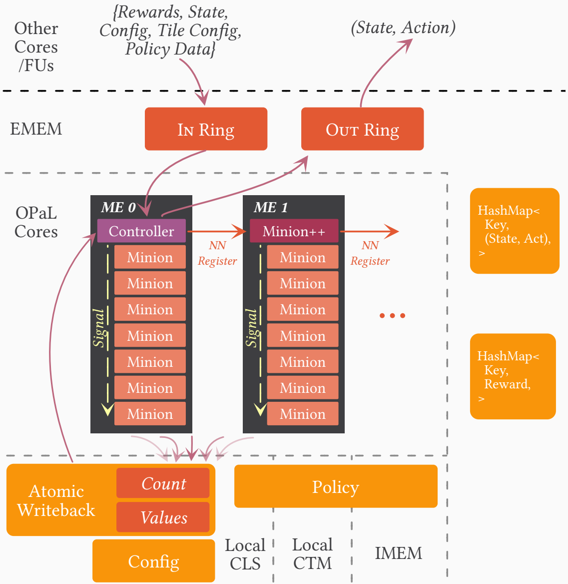
Designs: How to exploit on-NIC parallelism?

- Netronome SmartNICs *very* multi-core (NFP-6480).
  - NetFPGAs also allow creating separate, effectively async functional units.
- Two ways to take advantage:
  - Available threads process *Ind*ependently.
  - Available threads *CoOp*erate on each inference or learning task.
- Basic algorithm:
  - (Parallel) action compute.
  - Output action.
  - Check for trace in progress for this input.
  - If found: compute δ, do (parallel) policy update.

Designs: *Ind* (on NFP)



Designs: *CoOp* (on NFP)



Evaluation

Metrics of interest

Versus commodity hosts…

- State-Action/Update latency
- Online/Offline throughput
- Impact on cross-traffic
- Device resource use

On large-ish policies (20D state, 10 actions, bias+(7×1D, 8×2D, 1×4D)).

Latency

Datatype	Machine/FW	State-Action Latency (μs)			State-Update Time (μs)		
		Median	99^{th}	99.99^{th}	Median	99^{th}	99.99^{th}
Float	Collector	515.94	606.06	725.03	606.06	636.82	833.99
	MidServer	1069.07	1125.1	1508.0	1260.04	1605.99	1719.864
Int32	OPaL-*Ind*	185.133	185.533	186.213	230.840	231.347	232.227
	OPaL-*CoOp*	**34.347**	**34.520**	**34.573**	**62.000**	**62.440**	**63.120**

Lower latency with just one (slower) core.

One NFP island $\implies$ 15 × median S→A speedup.

Far tighter tail than host offload!

Latency—Bit Depth

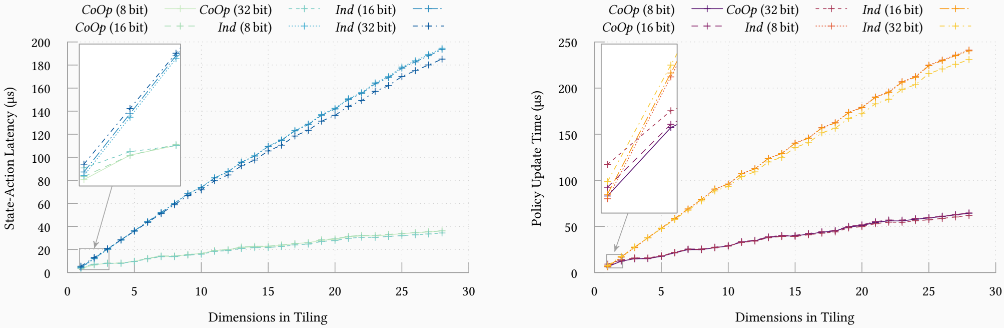


Figure 3: *OPaL action and update latencies based on work size (crossover at 3-dim, 10-dim).*

Latency—Core Count

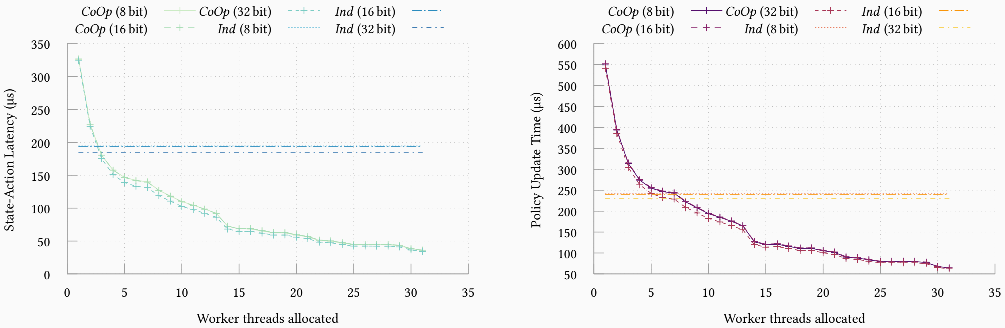
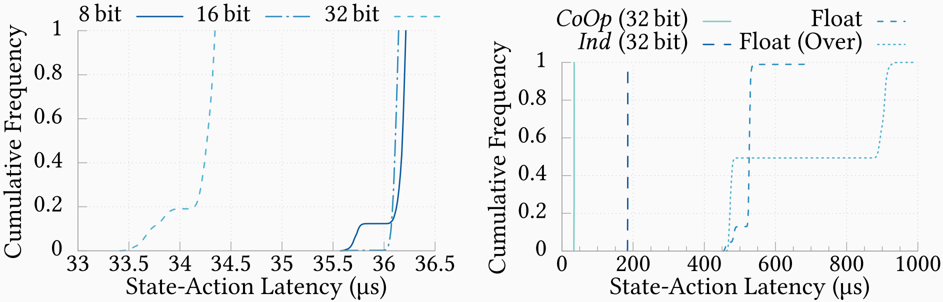


Figure 4: *OPaL action and update latencies based on worker count (crossover at 3-core, 8-core).*

Examining Tail Latencies



(a) *CoOp latency CDFs*

(b) *OPaL and host latency CDFs*

Figure 5: *Cumulative state-action latency plots for OPaL and host-based execution.*

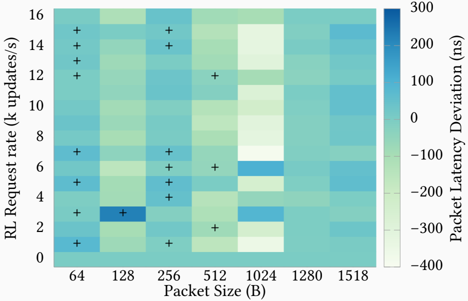
Throughput

Datatype	Machine/FW	Workers	Throughput (k actions/s)		Throughput/core (k actions/s)	
			Offline	Online	Offline	Online
Float	Collector	4	7.673(49)	1.627(31)	1.918(12)	—
	MidServer	6	5.584(30)	0.791(12)	0.931(5)	—
Int32	OPaL-*Ind*	32	**172.875(229)**	4.333(5)	**5.402(7)**	—
	OPaL-*CoOp*	32	29.166(173)	**16.141(73)**	0.911(5)	**0.504(2)**

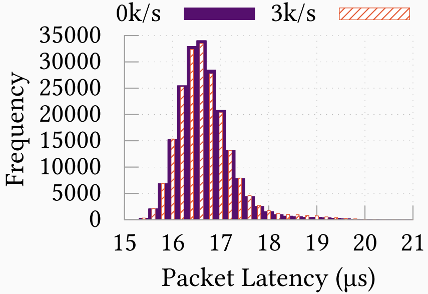
In-NIC and quantised offers higher throughput per core.

*Par*allel *Sar*sa key to maximising online throughput.

Impact on cross-traffic



(a) *Deviations in 99^th percentile RTTs.*



(b) *128 B outlier (99^th +222 ns)*

Figure 6: *Effects on tail latency of cross-traffic—typically sub-78 ns.*

Resource Use

Firmware	EMEM		EMEM Cache		IMEM		i5.CLS		i5.CTM	
	MiB	%	KiB	%	KiB	%	KiB	%	KiB	%
Base P4	6776.67	88.24	268.52	2.91	858.28	10.48	0.00	0.00	0.00	0.00
Ind(1)	6780.21	88.28	2541.08	27.57	1263.28	15.42	24.75	38.67	94.25	36.82
Ind(4)	6780.22	88.28	2545.33	27.62	1263.28	15.42	51.18	79.97	107.00	41.80
CoOp(1)	6779.12	88.27	1773.59	19.24	1263.28	15.42	22.41	35.01	90.00	35.16
CoOp(4)	6779.12	88.27	1769.84	19.20	1263.28	15.42	52.16	81.49	90.00	35.16

Network deployment/configurability

- *Ind*: 27 µs
- *CoOp*: 54–238 µs
- **New policy data?** Just memcopies.
- Only design, bit depth, max policy sizes need recompile.
- Can mix and match agent types in the network, export learned policy over control plane.

Takeaways:

Online in-NIC RL is possible!

Order-of-magnitude latency improvement over offloading, higher online throughput.

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

Future work: use-cases (AQM, DDoS prevention & accuracy), NetFPGA, transfer learning.

Questions?

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Scheduler performance

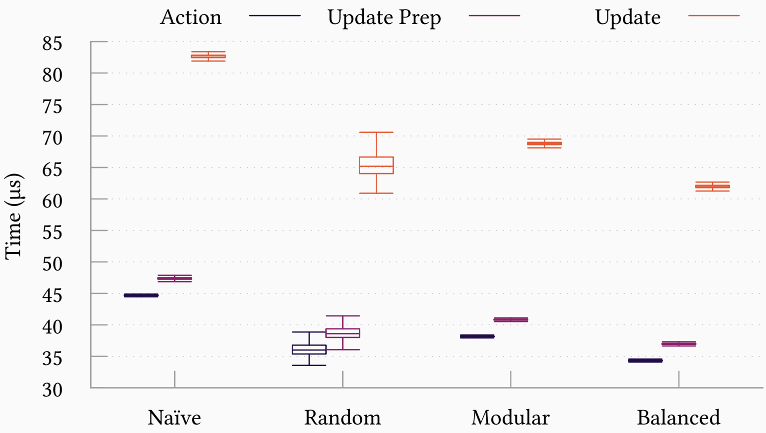

Figure 7: *Action/update compute times in a 32 bit CoOp agent under different work schedulers.*

Per-worker throughput

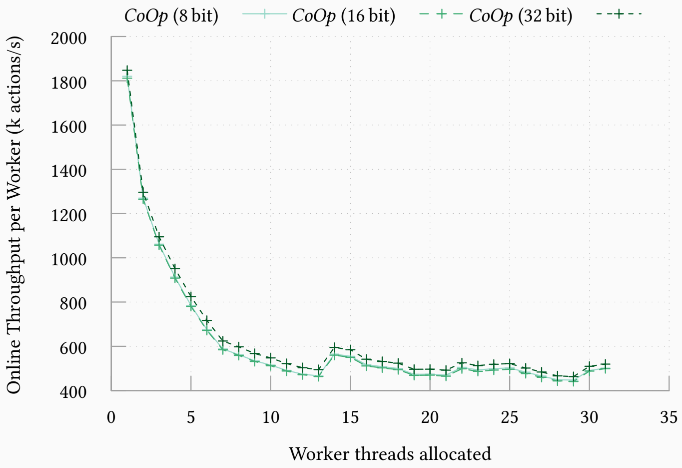

Figure 8: *Throughput per added worker in a CoOp agent.*

Latency—All OPaL

Datatype	Machine/FW	State-Action Latency (μs)			State-Update Time (μs)		
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	OPaL-*CoOp*	**34.347**	**34.520**	**34.573**	**62.000**	**62.440**	**63.120**
Int16	OPaL-*Ind*	193.427	193.787	194.587	240.333	240.840	241.560
	OPaL-*CoOp*	36.147	36.240	36.280	64.667	65.080	65.973
Int8	OPaL-*Ind*	194.520	194.840	195.240	241.173	241.707	242.760
	OPaL-*CoOp*	36.227	36.307	36.347	64.333	64.867	65.693

Throughput—All OPaL

Datatype	Machine/FW	Workers	Throughput (k actions/s)		Throughput/core (k actions/s)	
			Offline	Online	Offline	Online
Float	Collector	4	7.673(49)	1.627(31)	1.918(12)	—
	MidServer	6	5.584(30)	0.791(12)	0.931(5)	—
Int32	OPaL-*Ind*	32	**172.875(229)**	4.333(5)	**5.402(7)**	—
	OPaL-*CoOp*	32	29.166(173)	**16.141(73)**	0.911(5)	**0.504(2)**
Int16	OPaL-*Ind*	32	165.437(118)	4.161(4)	5.170(4)	—
	OPaL-*CoOp*	32	27.664(36)	15.471(54)	0.865(1)	0.483(2)
Int8	OPaL-*Ind*	32	164.524(142)	4.147(5)	5.141(4)	—
	OPaL-*CoOp*	32	27.631(101)	15.552(68)	0.863(3)	0.486(2)

References i

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