TECHNISCHE UNIVERSITÄT WIEN

LFQ: Online Learning of Per-flow Queuing Policies using Deep Reinforcement Learning

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Fair Queuing

- Separate each flow in separate queue
- No flow can “steal” bandwidth
- Popular implementation for Linux: `fq`

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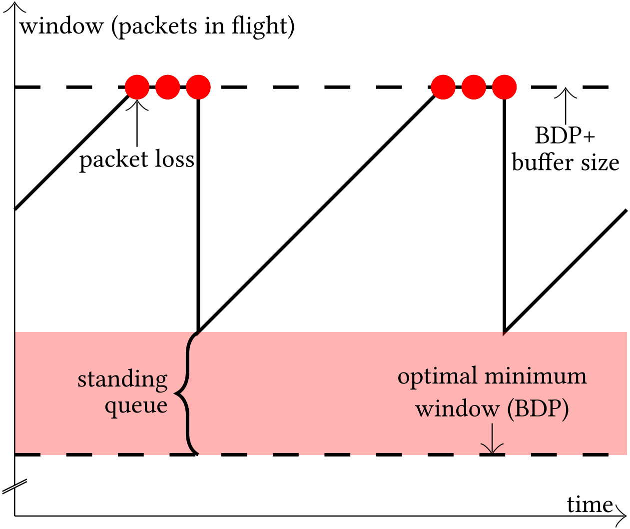
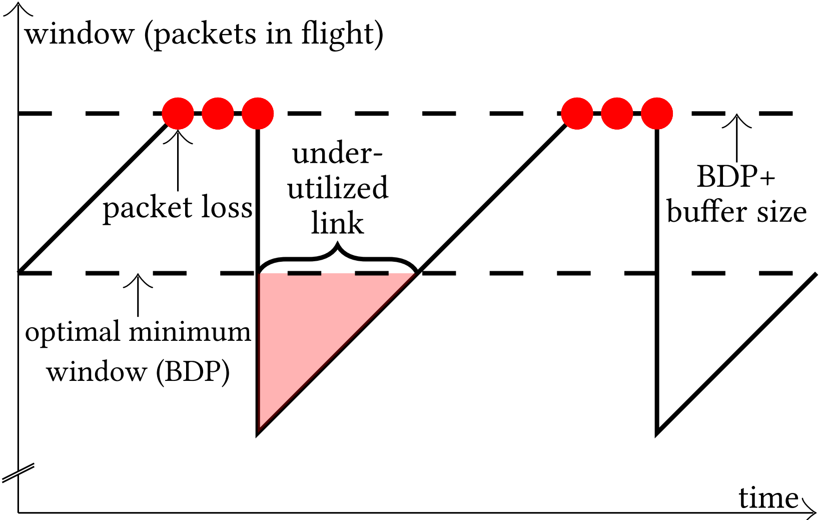
Static buffer size:

Buffer often too large or too small

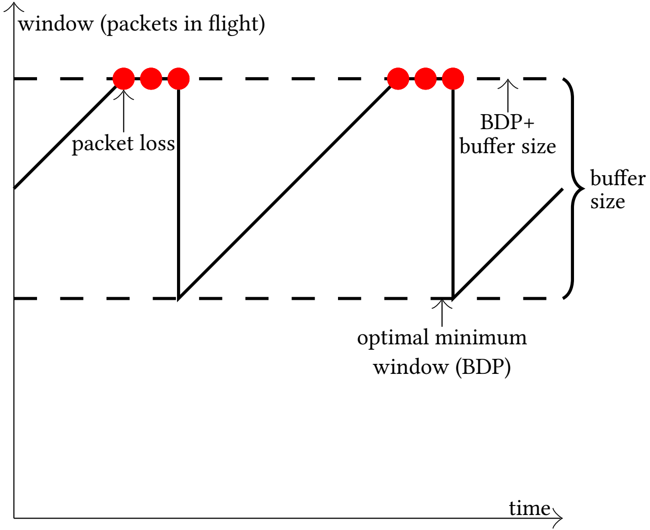
Buffer too large



Buffer too small



Buffer perfect



Deep Reinforcement Learning for Buffering

- Have a separate queue for each flow in a switch/router (fair queuing)
- Define some reward function (like high throughput, low delay)
- Use **Deep Reinforcement Learning**
  - to **fingerprint** each flow
  - and to use the **correct buffer size** for the flow **based on experience**, which **maximizes the reward**
- We call it *Learning Fair Queuing*

Reward

$$Reward = throughput - \alpha \times queue\ size$$

Input features

- queue size
- standard deviation of the queue size
- maximum allowed buffer size
- rate of incoming data
- rate of outgoing data
- time since the last packet loss

Neural Network

- It is a regression problem: Predict optimal buffer size for the flow based on the inputs
- Fully connected neural network with three layers and leaky ReLU
- Outputs optimal maximum buffer size each time packet is received
  - To save compute it is possible, for example, only output optimum buffer size every 100 ms

Implementation

- ns-3 for network simulation
- Pytorch's C++ API for Deep Learning
- Integrate Pytorch into ns-3
- Develop queuing discipline based on fair queuing
- Each flow is managed by Deep Reinforcement Learning

Offline Learning

- Randomly sample bandwidth, delay, congestion control and flow duration
- Simulate each flow continuously using the optimal buffer size output by the Deep Reinforcement Learning
- For each flow, at a random time, launch experiment (A/B testing):
    - Continue one experiment with current buffer size +1 packet and one with current buffer size -1 packet (two different experiments)
- Let the neural network learn which buffer size achieved the higher reward
- Train using L1 loss (mean absolute error), using a couple of results together as a batch

Training takes several hundred thousand flows to converge.

Measuring success

Should learn

- Larger bandwidth $\rightarrow$ larger buffer
- Larger delay $\rightarrow$ larger buffer
- New Reno Congestion Control should get bigger buffer than BIC

Correlations

Correlations calculated of each of the above plots:
Correlation of 100% $\rightarrow$ Our Reinforcement Learning system learned successfully

Table: Correlation between bandwidth/delay of the link and output buffer size.

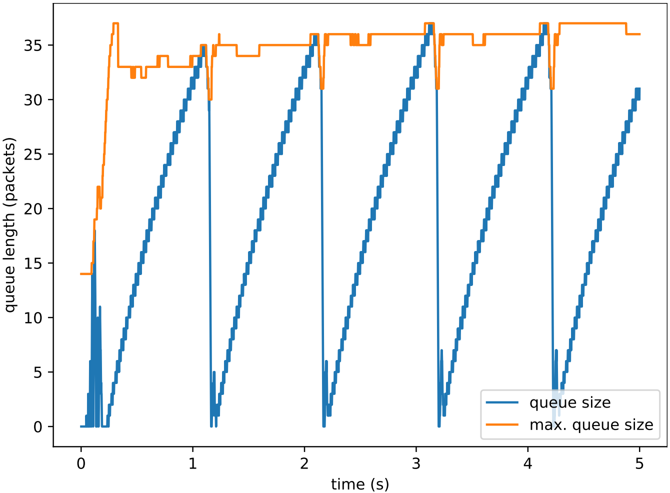
Congestion control	bandwidth	delay
New Reno	98.3%	99.1%
BIC	80.2%	90.2%

Average queue sizes

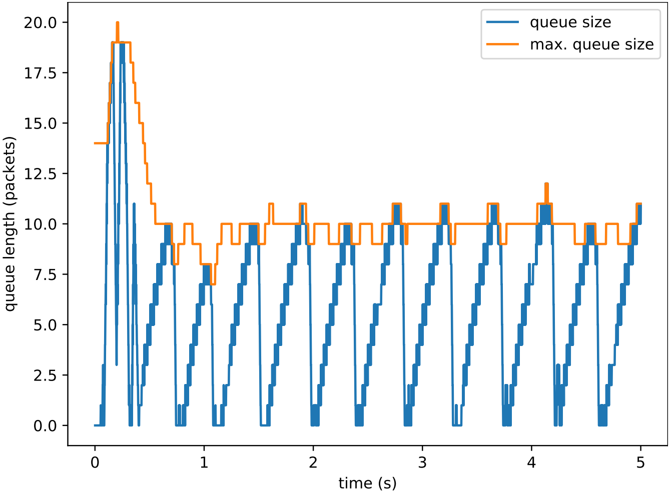
Average queue is smaller for New Reno: This is expected since it has a larger multiplicative decrease parameter!
$\rightarrow$ New Reno needs a larger buffer on average so that the buffer never becomes empty. Our mechanism learned that!

Congestion control	avg. max. queue length
New Reno	22
BIC	8

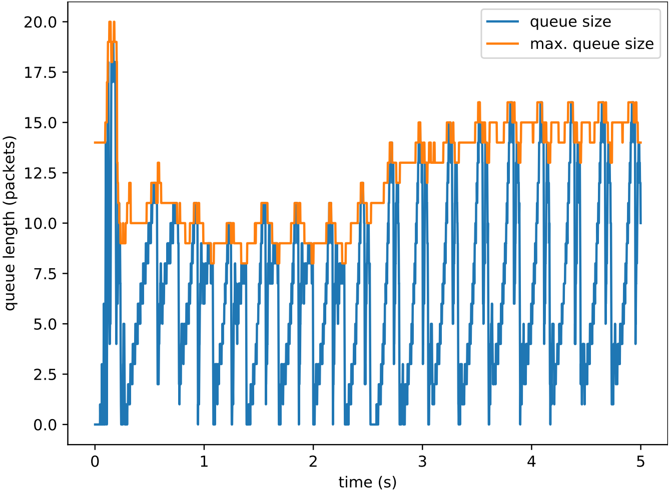
25 Mbit/s, 15 ms, New Reno, LFQ



6 Mbit/s, 15 ms, New Reno, LFQ



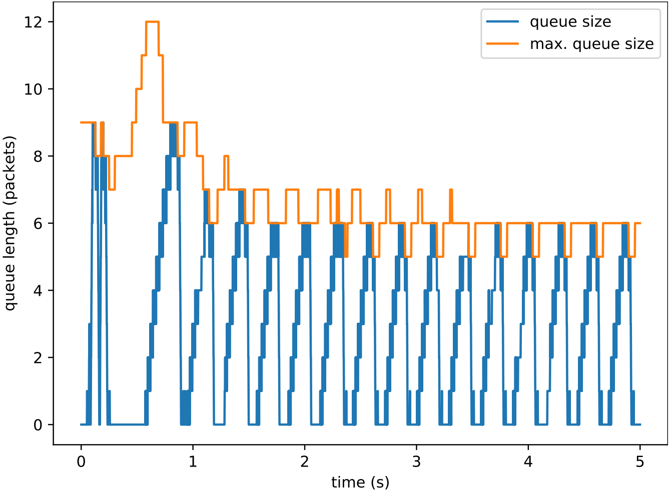
25 Mbit/s, 15 ms, BIC, LFQ



Average queue sizes

Congestion control	avg. max. queue length
New Reno	13
BIC	5

6 Mbit/s, 15 ms, New Reno, LFQ



Online Learning

Same as Offline Learning except:

- Don't do A/B testing
- Instead: Use second neural network that outputs expected reward (*Critic Network*) (trained using L2 loss (mean squared error).
- Either perform experiment A **or** experiment B (either current buffer size -1 packet or $+1$ packet)
- If result was better than what the Critic Network expected, let first neural network (*Actor Network*) learn to output this buffer size in the future.

Training takes longer (several million training flows)

Correlations

Table: Correlation between bandwidth/delay of the link and output buffer size.

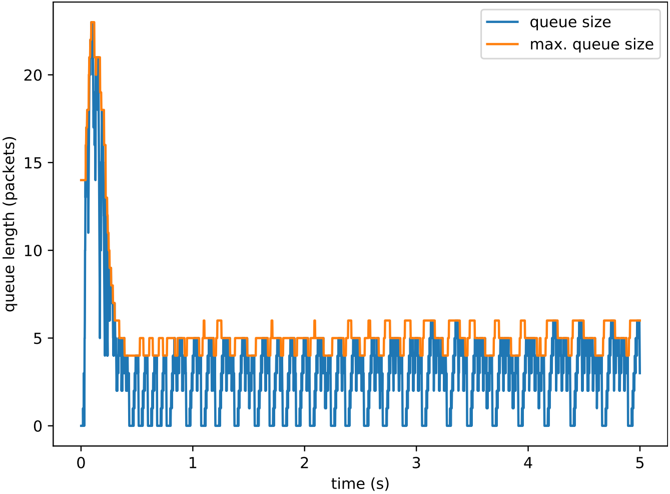
Congestion control	bandwidth	delay
New Reno	86.1%	87.7%
BIC	72.9%	73.6%

Average queue sizes

Congestion control	avg. max. queue length
New Reno	14
BIC	8

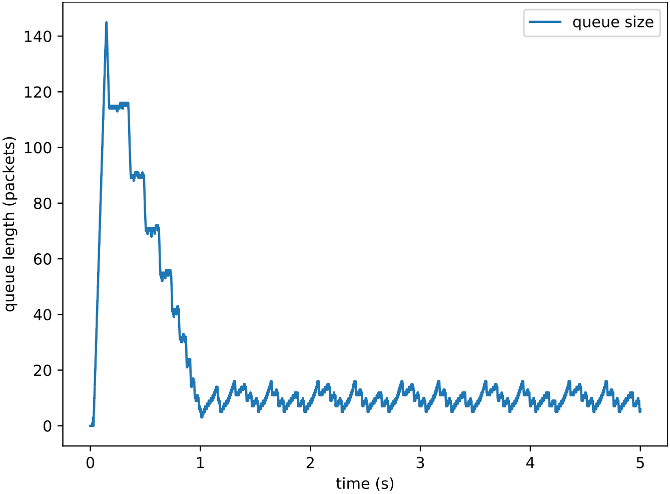
Example: Our solution

15 Mbit/s bandwidth, 5 ms delay



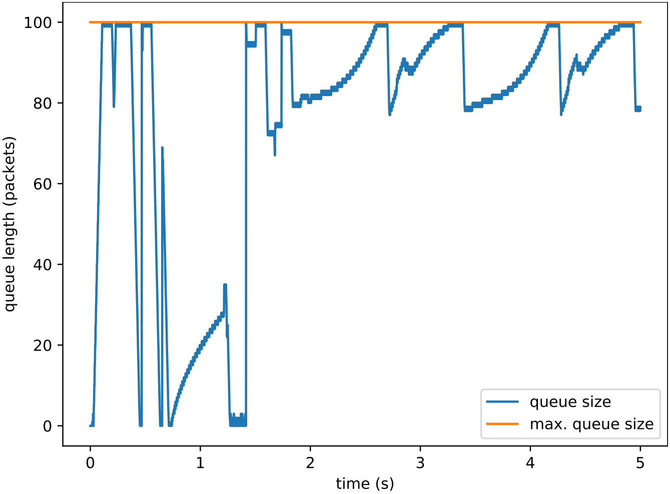
Example: FqCoDel (default on home routers)

15 Mbit/s bandwidth, 5 ms delay



Example: Fifo (default on Linux)

15 Mbit/s bandwidth, 5 ms delay



Systematic comparison

Table: 400 experiments; delay 5 – 25 ms; bandwidth 5 – 25 Mbit/s; New Reno and Bic Congestion Control. Results averaged.

	avg. throughp.	queue size max.	queue size avg.
LFQ, offline $\alpha = 0.01$	13.4	23.9	7.7
LFQ, offline $\alpha = 10$	12.5	12.7	3.4
LFQ, online $\alpha = 10$	12.8	16.1	4.5
FqCoDel	13.7	155.4	15.4
fq 100	11.7	100	51.1
fq 1000	11.9	1000	630.4

Observations

- Scaling of features very important
- Pytorch better to integrate with other code (ns-3) than TensorFlow
- We thought simulating a flow in ns-3 would be faster than running it in the real world. It is not.

Conclusion

- LFQ is based on fair queuing
- It fingerprints each flow
- It learns to optimize a reward function
- It achieves high throughput and low delay when compared to competing solutions
- It has low computational overhead
- We envision deployment close to end users (for example on home routers)

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