An experimental study of the learnability of congestion control

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Designing congestion-control protocols today

- Formulate a mental model of the target network and application workload
- Decide on the protocol's goal
- Design a protocol to achieve this goal on the target network
- Can either be implicit or explicit

But, the model is always wrong!

- Lost throughput due to stochastic loss
- Bufferbloat when queues are incorrectly sized
- Diminished fairness in small-packet regimes
- Incast in datacenters



Our work

- Can we formalize this design process?
- Quantify the consequences of model mismatch?

Approach

- Specify a training scenario.
 - Topology
 - Locations of senders and receiver
 - Application workload
 - Buffer size and queuing discipline
- Specify an objective function.
- Synthesize protocol automatically.
- Evaluate on a testing scenario inside ns-2

Automated protocol synthesis

- Find best protocol, given an imperfect network model.
- Unfortunately, problem is NEXP-complete.

Tractable Attempts at Optimal

- Rely on Remy [?] to produce Tractable Attempts at Optimal (TAO) congestion-control protocols.
- Approaches upper bounds on throughput and lower bounds on delay.

Training scenario:

Link speed 32 Mbits/sec

minimum RTT 150 ms

Topology Dumbbell

Number of senders 2

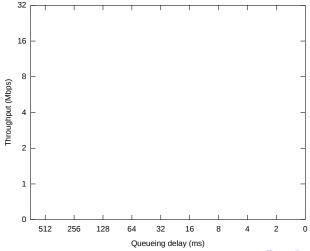
Workload 1 sec ON/OFF times

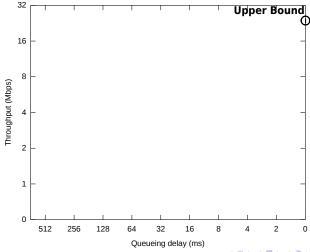
Buffer size 5 BDP

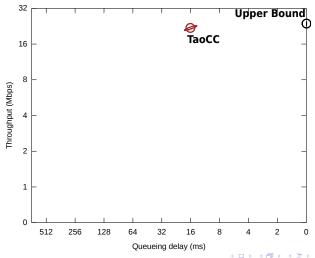
Objective function $\sum \log(\text{throughput}) - \log(\text{delay})$

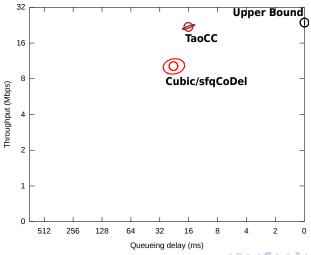
Testing scenario identical to training scenario

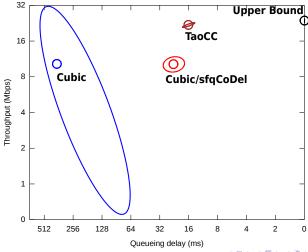






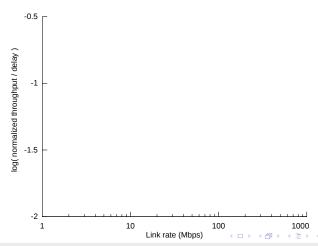


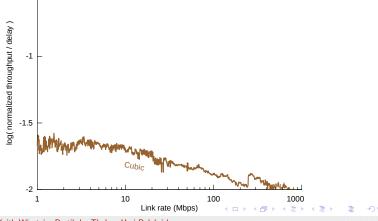




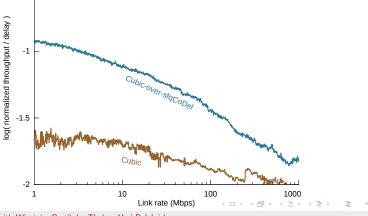
Tao	Link rates	RTT	Senders	ON/OFF time	Topology
1000x	1-1000 Mbps	150 ms	2	1 sec	Dumbbell
100x	3.2-320 Mbps	150 ms	2	1 sec	Dumbbell
10x	10-100 Mbps	150 ms	2	1 sec	Dumbbell
2x	22-44 Mbps	150 ms	2	1 sec	Dumbbell

Table: Training scenarios for forwards-compatibility experiment

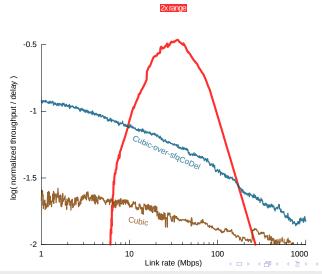


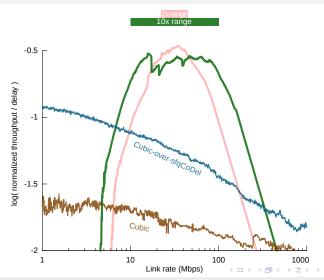


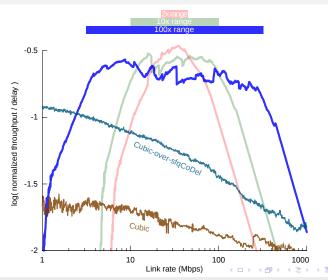
-0.5

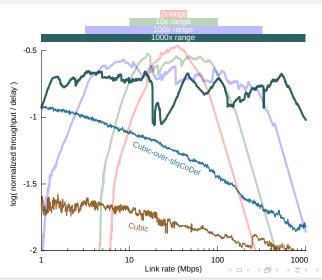


-0.5

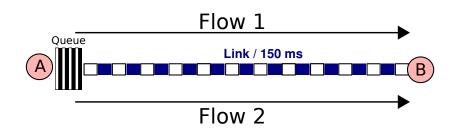




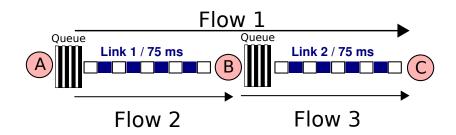


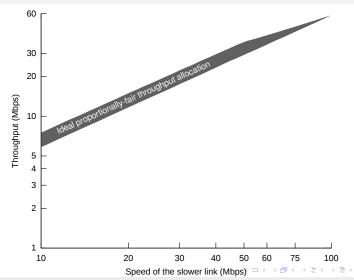


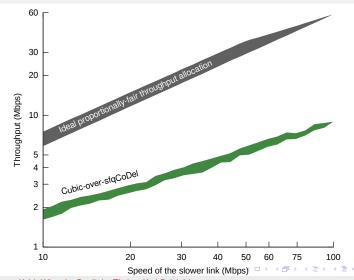
One bottleneck

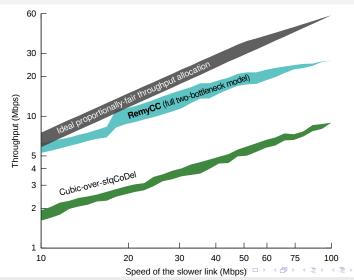


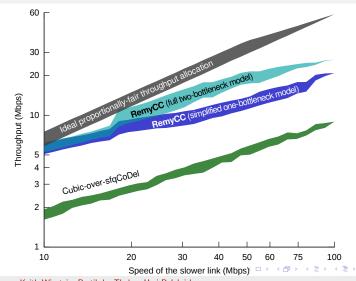
Two bottlenecks



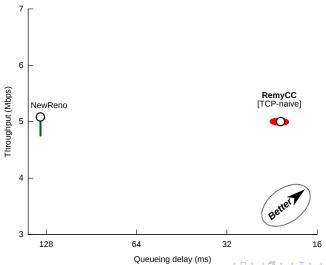




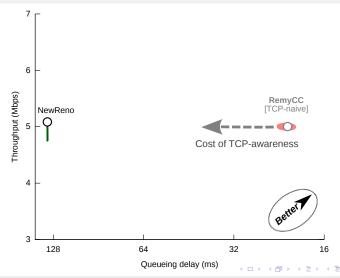




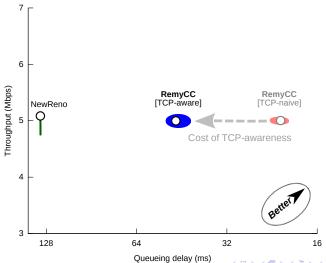
RemyCC competing against itself



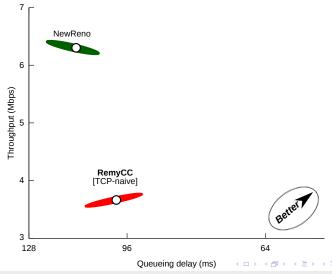
RemyCC competing against itself



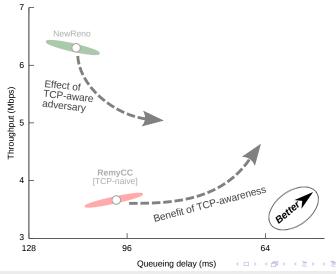
RemyCC competing against itself



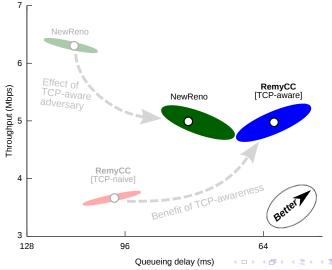
RemyCC competing against TCP NewReno



RemyCC competing against TCP NewReno



RemyCC competing against TCP NewReno



Can applications with different objectives coexist?

Tpt. Sender: A throughput-intensive sender

$$log(throughput) - 0.1 * log(delay)$$
 (1)

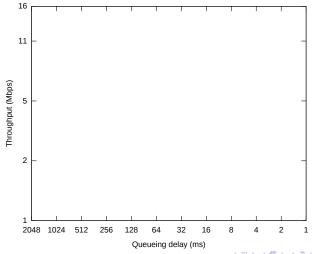
Lat. Sender: A latency-sensitive sender

$$log(throughput) - 10.0 * log(delay)$$
 (2)

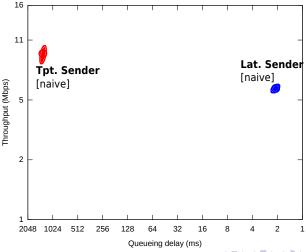
Running over a FIFO queue



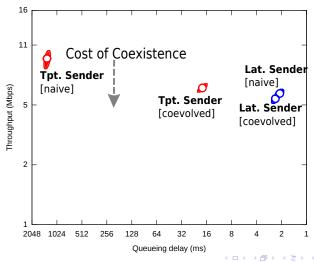
Training for diversity has a cost ...



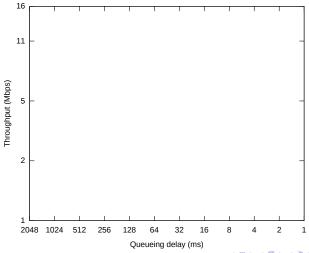
Training for diversity has a cost ...



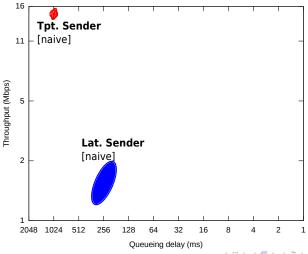
Training for diversity has a cost ...



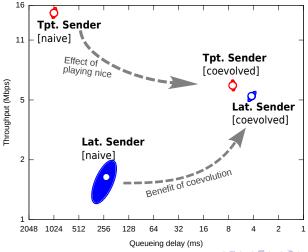
but, benefits the docile sender



but, benefits the docile sender



but, benefits the docile sender



Related Work

- Probably approximately correct learning
- Transfer learning
- Machine-generated congestion control

Limitations and future work

- Generalizability to more complex topologies?
- Better characterization of gap from optimal
- ▶ Do results change if we learn in-network behavior as well?
- Model mismatches between simulation and the real world