Towards Integrating Formal Methods into ML-Based Systems for Networking

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Machine learning is scalable and adaptable

But…

How generalizable is a machine learning model?

How do we make sure a model is trustworthy when used in real world?
ML-based solutions lack correctness guarantees

ML-based solutions may...
- result in implausible outputs
- perform worse than simple heuristics
- contradict common sense
Formal Methods leverages knowledge to generate correct results

...but, it doesn’t scale
Towards Integrating Formal Methods into ML-Based Systems for Networking

Solutions with both correctness and scalability
Fine-grained telemetry is required for network managements, but hard to get
Coarse-grained telemetry in switches

Maximum queue length with 50ms granularity
Coarse-grained telemetry in switches

Periodic queue length with 50ms granularity
Coarse-grained telemetry in switches

Per-port packet drop count with 50ms granularity
Coarse-grained telemetry in switches

Per-port packet sent count with 50ms granularity
Network telemetry imputation

Coarse-grained measurements with 50ms granularity

Fine-grained queue length with 1ms granularity
Coarse-grained measurements with 50ms granularity

Fine-grained queue length with 1ms granularity

Network Telemetry Imputation: recovering fine-grained time-series from coarse-grained ones
Potential solutions: ML or Formal Methods

Coarse-grained measurements → Transformer → Fine-grained queue length

Coarse-grained measurements → Constraints → SMT Solver → Fine-grained queue length

Switch operation rules
A transformer can learn correlations, but the output lacks correctness.
A transformer can learn correlations, but the output lacks correctness.

Coarse-grained measurements

Imputed fine-grained queue length

Ground truth

Max Qlen

Periodic Qlen

Port Pkt Sent

Port Pkt Drop

Imputed data
A transformer can learn correlations, but the output lacks correctness.
Formal Methods can find a plausible solution, but is hard to scale

Operation constraints:
- Scheduling algorithm
- Buffer management algorithm

Measurement constraints:
- The maximum queue length
- The periodic queue length

SMT Solver

Couldn’t finish in 24hrs for 1Gbps bandwidth
How to integrate them?

Challenges:

- No standard way
- ML models cannot easily ingest traditional rules or relationships
- Incorporating knowledge can increase the complexity of the learning process
Start from transformer
Knowledge augmented loss

Coarse-grained Time Series

Knowledge Augmented Loss

Training phase

Transformer

Imputed fine-grained queue length
Constraint enforcement module

Knowledge Augmented Loss

Training phase

Transformer

Inference phase

Constraints Enforcement Module

Coarse-grained Time Series

Imputed fine-grained queue length

Real Qlen
Max Qlen
Periodic Qlen
Port Pkt Sent
Port Pkt Drop

Max Qlen
Periodic Qlen
Ground truth
Imputed data
What next?

Integrating Formal Methods and ML
   Is there a better way of integrating them?
   What other network problems can benefit?

Generalize Network Telemetry Imputation
   What other telemetry metrics can be imputed?
   How do we impute real-time?