

# 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?

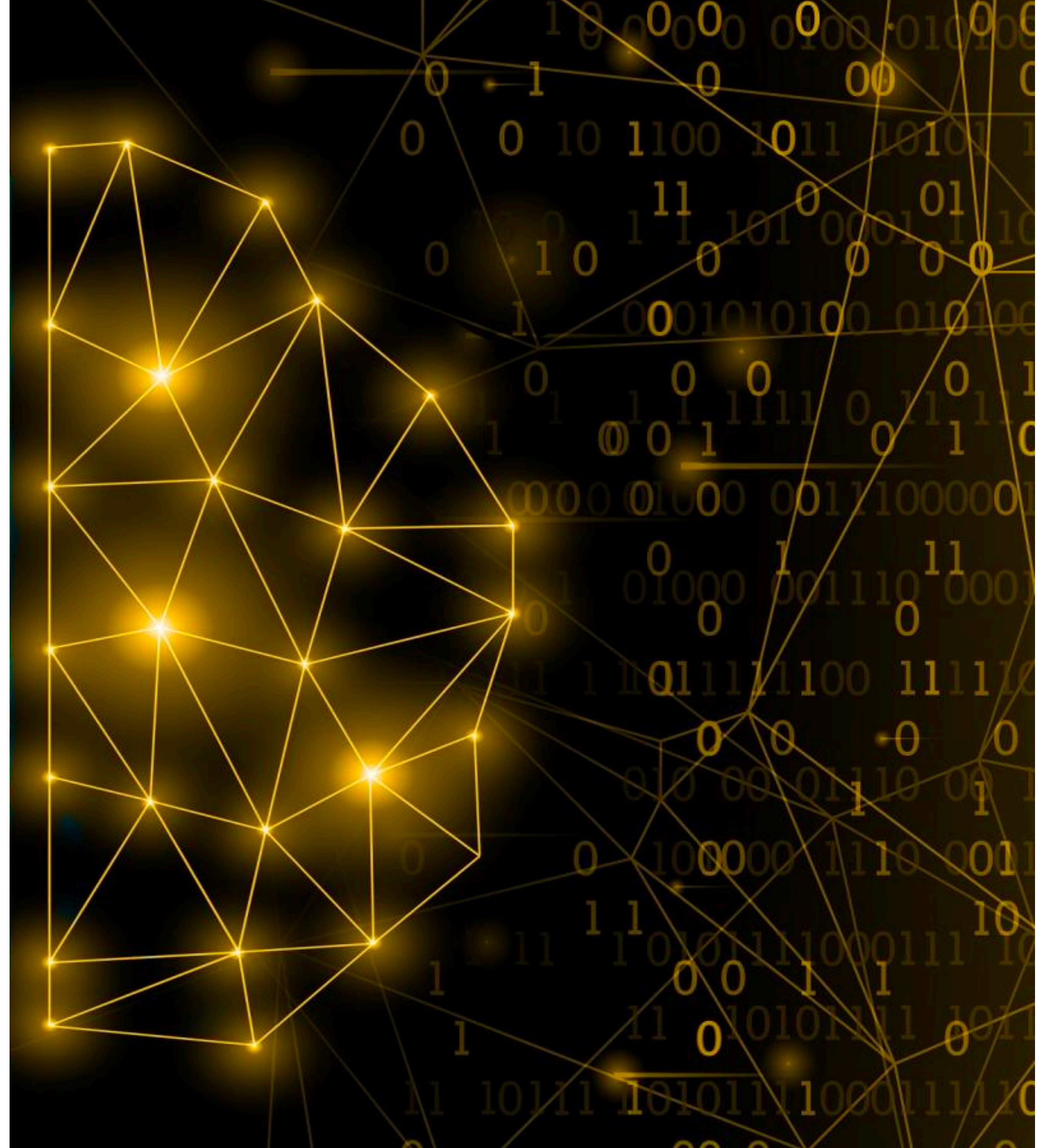




# ML-based solutions lack correctness guarantees

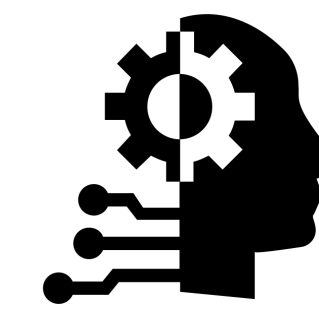
ML-based solutions may...

- result in implausible outputs
- perform worse than simple heuristics
- contradict common sense





Formal Methods leverages knowledge to generate correct results



Constraints



SMT Solver



Plausible output

...but, it doesn't scale







$$\psi_1(x) = \frac{1}{\sqrt{k_1}} (A_1 e^{ik_1 x} + A_2 e^{-ik_1 x}) \quad x < 0$$



$$S = \frac{1}{2} \int d^4 x \left( R + \frac{R^2}{6M^2} \right)$$

$$\frac{1}{2} R_{\mu\nu} = \frac{8\pi G}{c^4} T_{\mu\nu}$$

$$H|\psi(t)\rangle = i\hbar \frac{\partial}{\partial t} |\psi(t)\rangle$$

$$E = p^2 c^2 + m^2 c^4$$

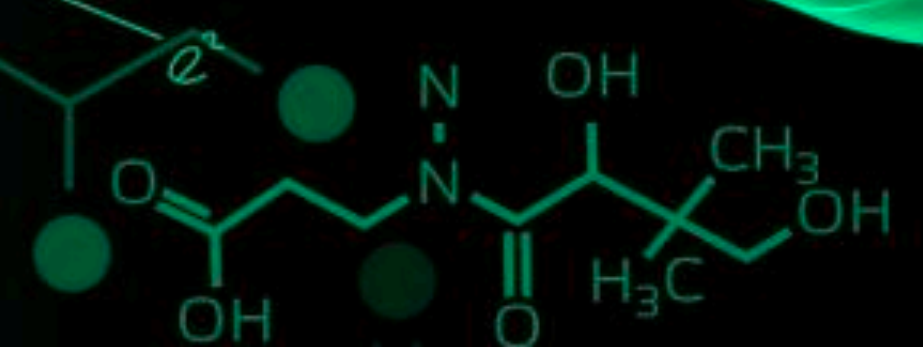
$$p = \hbar k = \frac{h\nu}{c} = \frac{h}{\lambda}$$

$$\frac{\delta(k_1 + k_2)}{k_i^2}$$

$e^-$



$$S_{fi} = \langle f | S | i \rangle$$





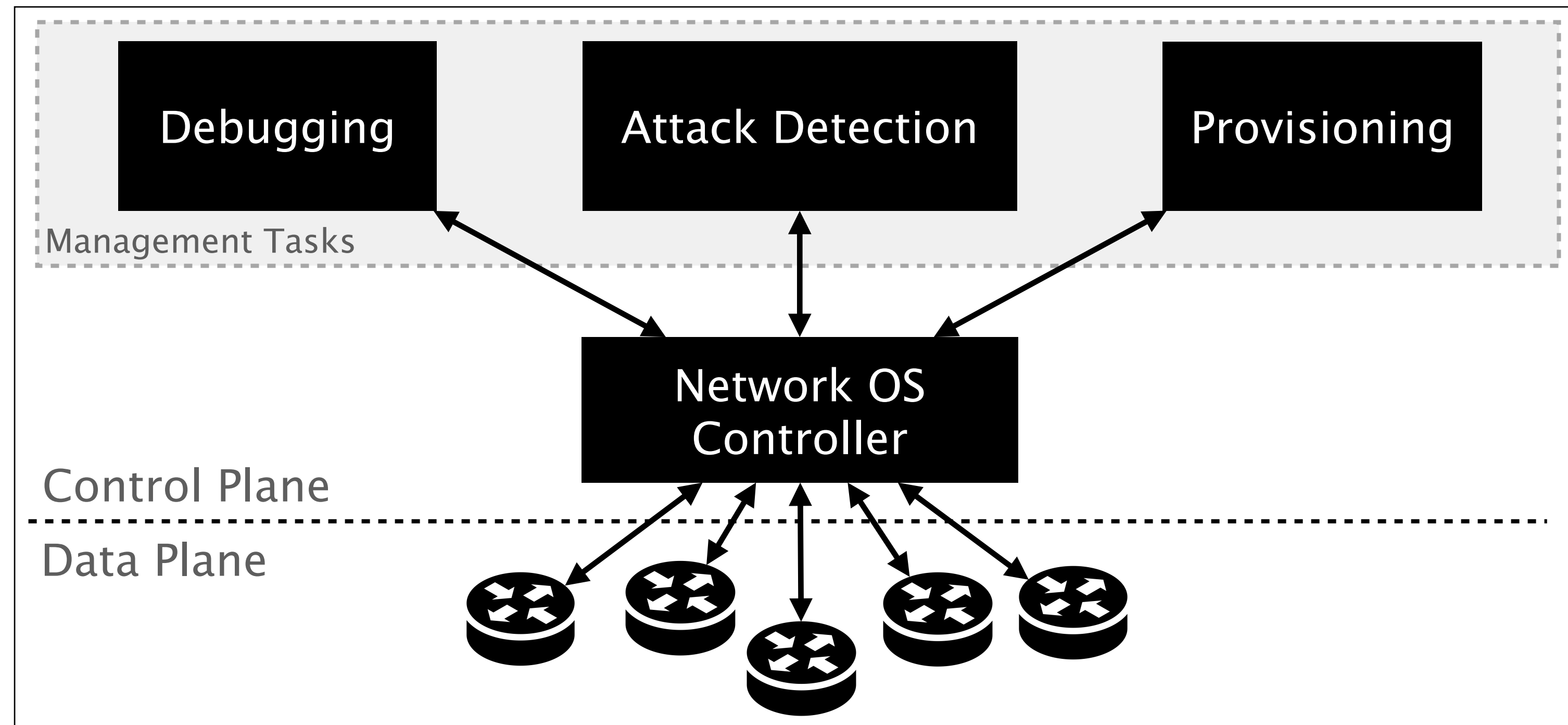
# Towards Integrating Formal Methods into ML-Based Systems for Networking

Formal Methods  
closed-forms

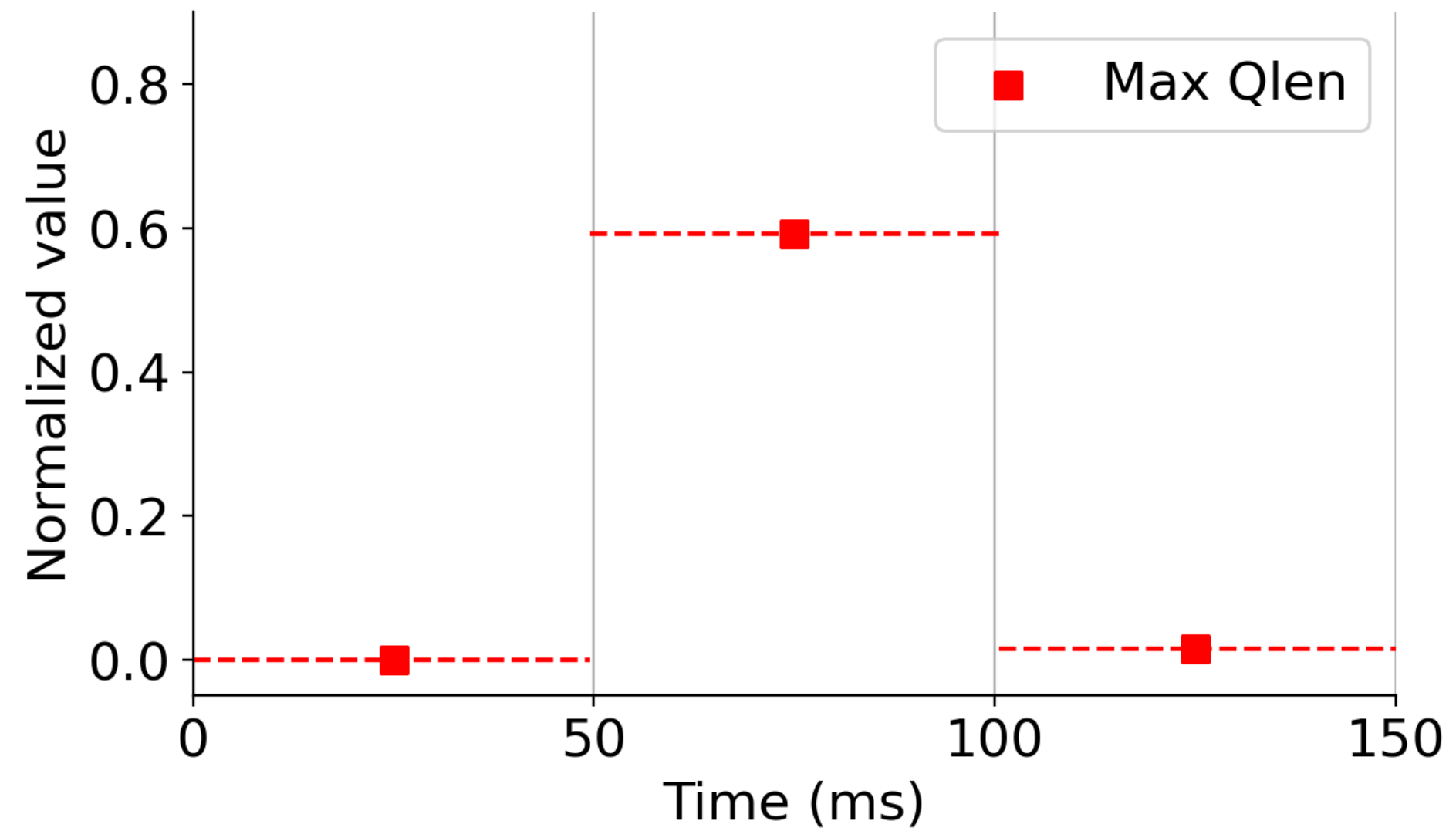
Machine Learning  
correlations

Solutions with both correctness and scalability

# Fine-grained telemetry is required for network managements, but hard to get



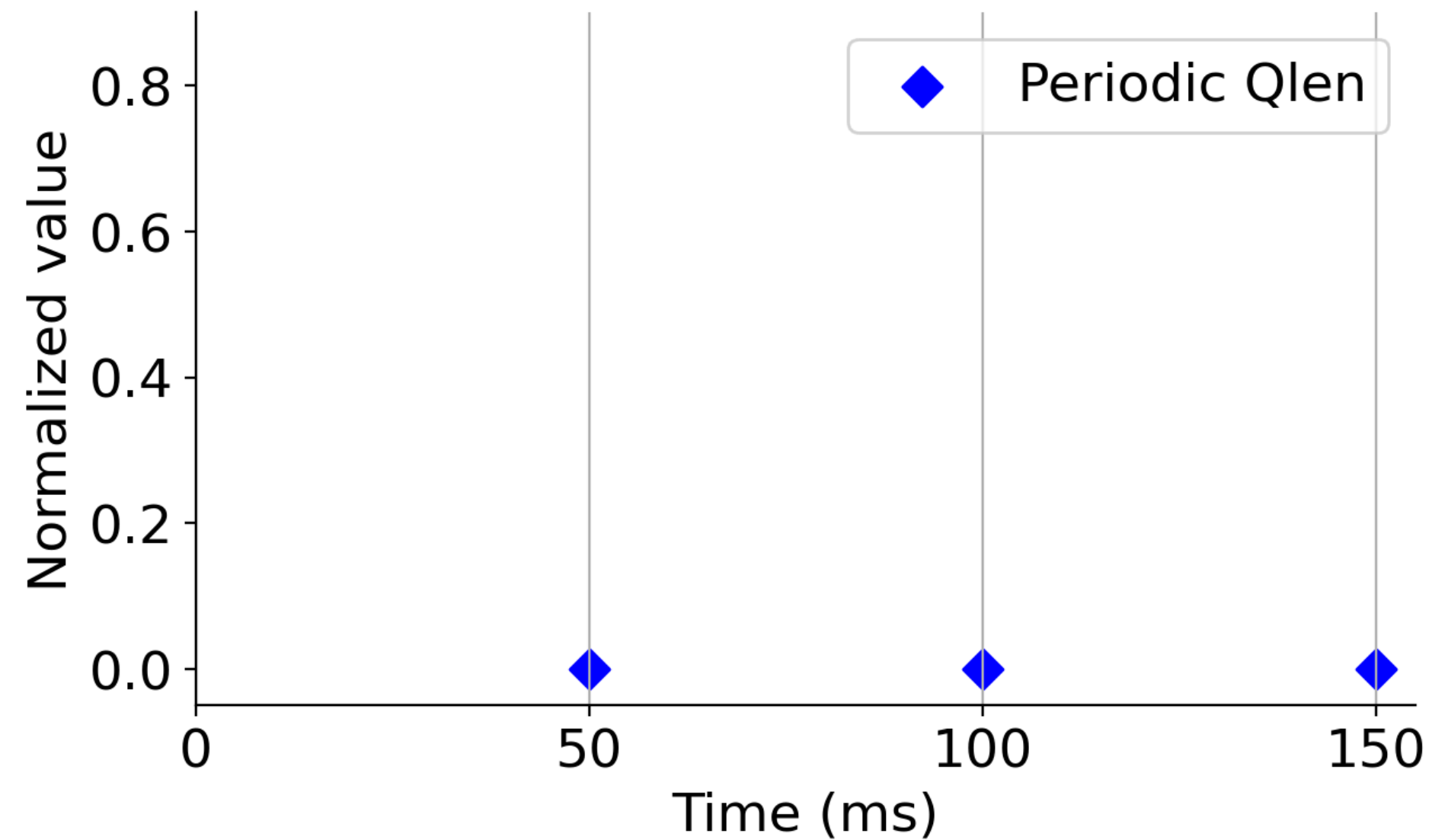
# Coarse-grained telemetry in switches



Maximum queue length  
with 50ms granularity



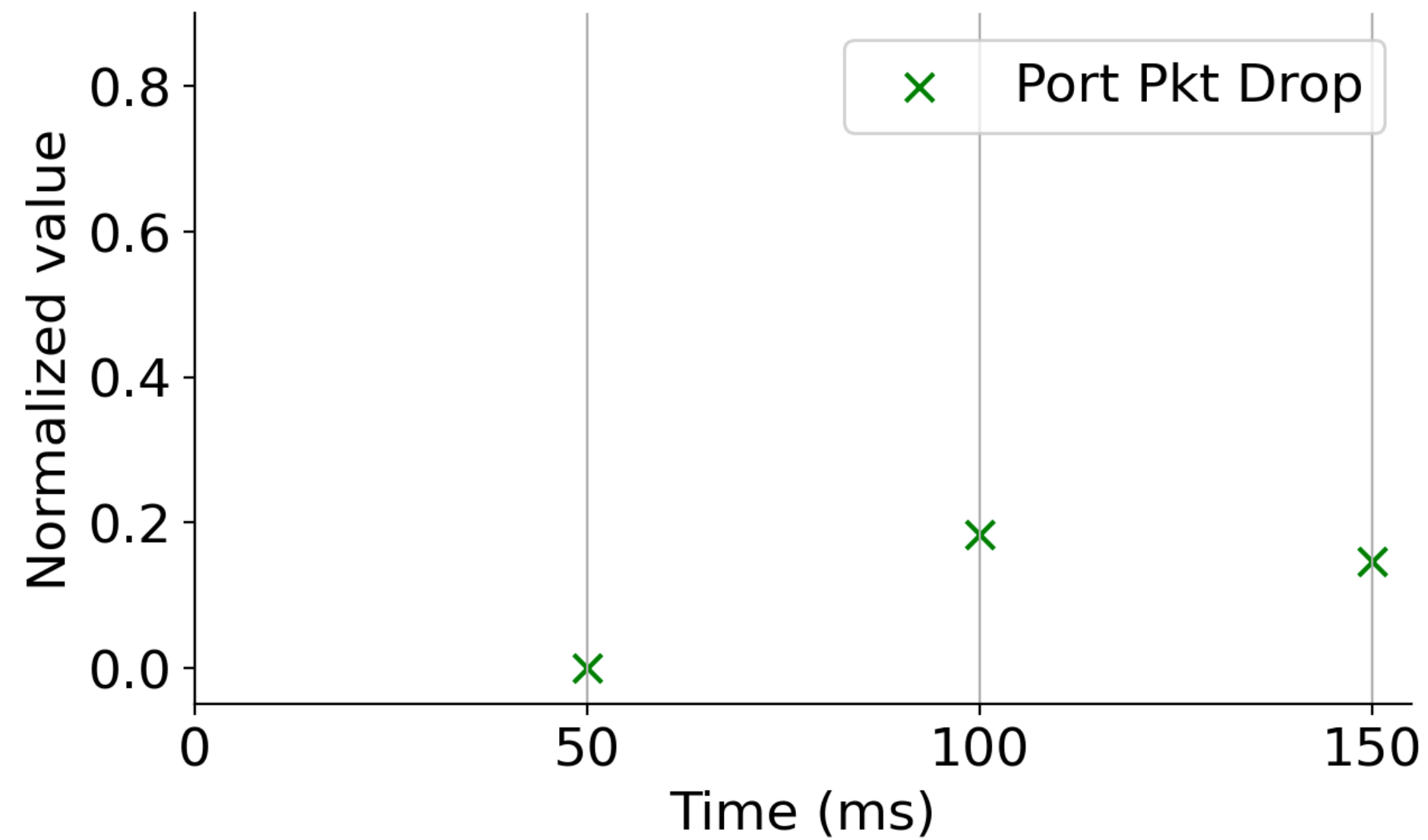
# Coarse-grained telemetry in switches



Periodic queue length  
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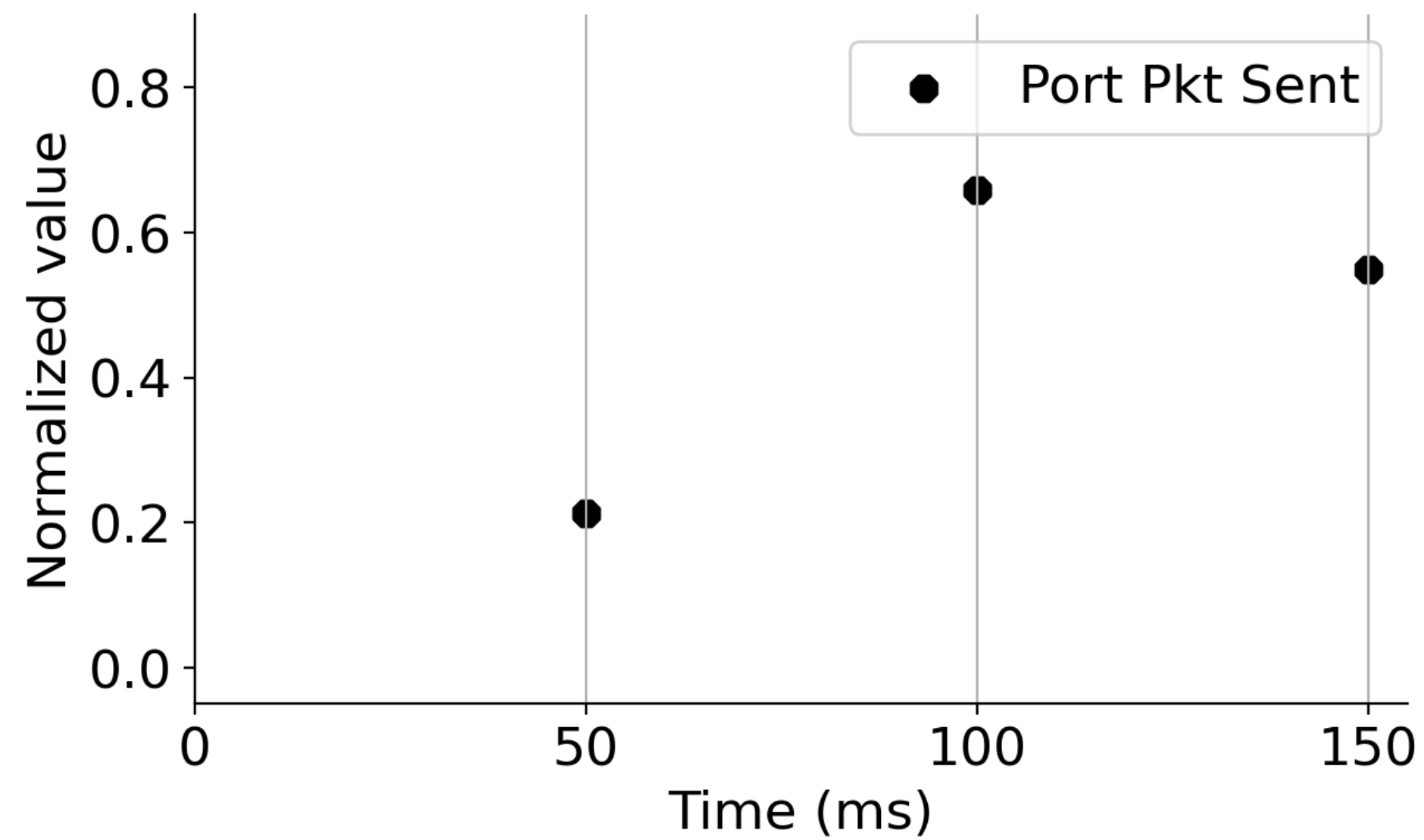
# Coarse-grained telemetry in switches



Per-port packet drop count  
with 50ms granularity



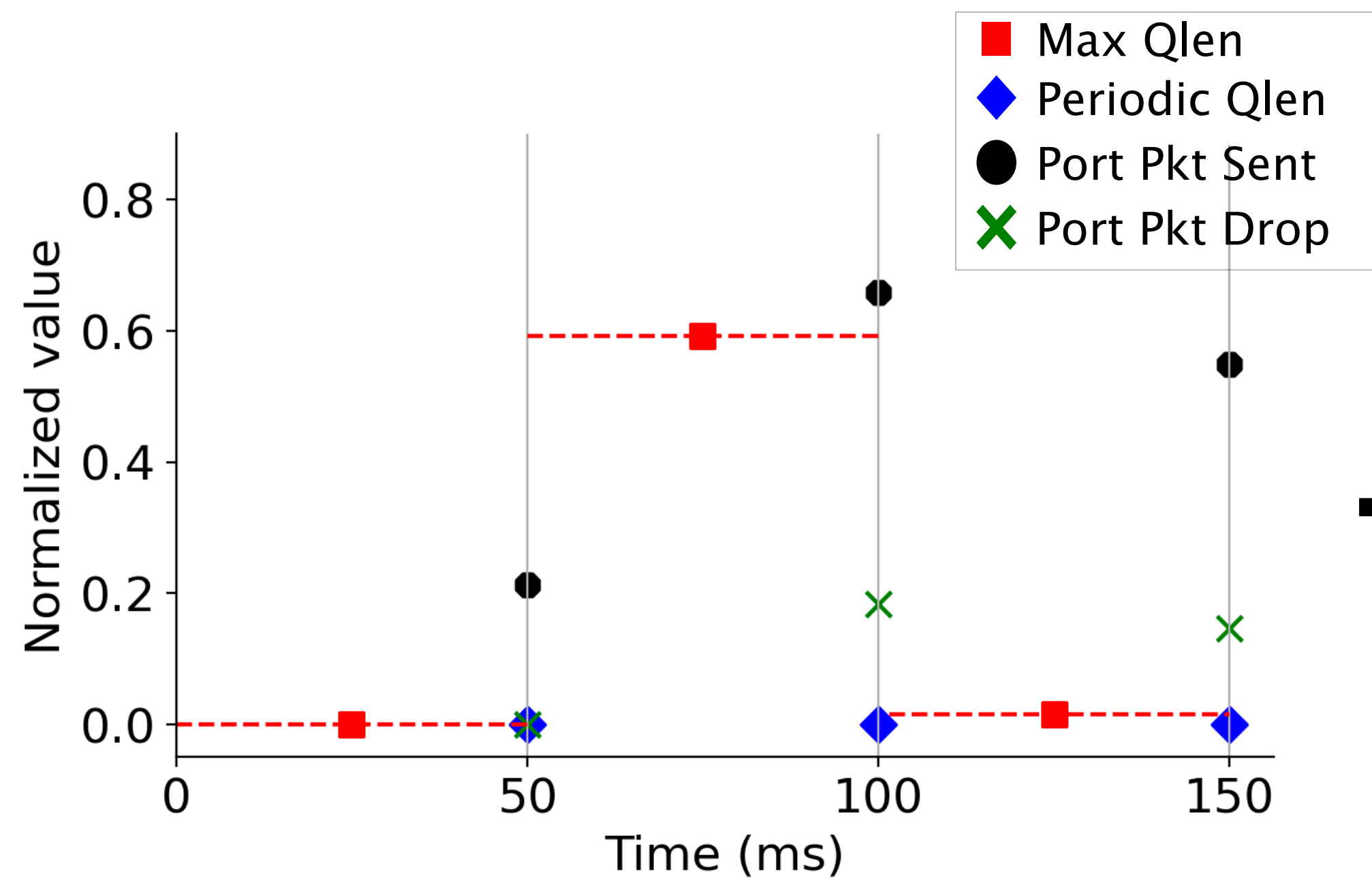
# Coarse-grained telemetry in switches



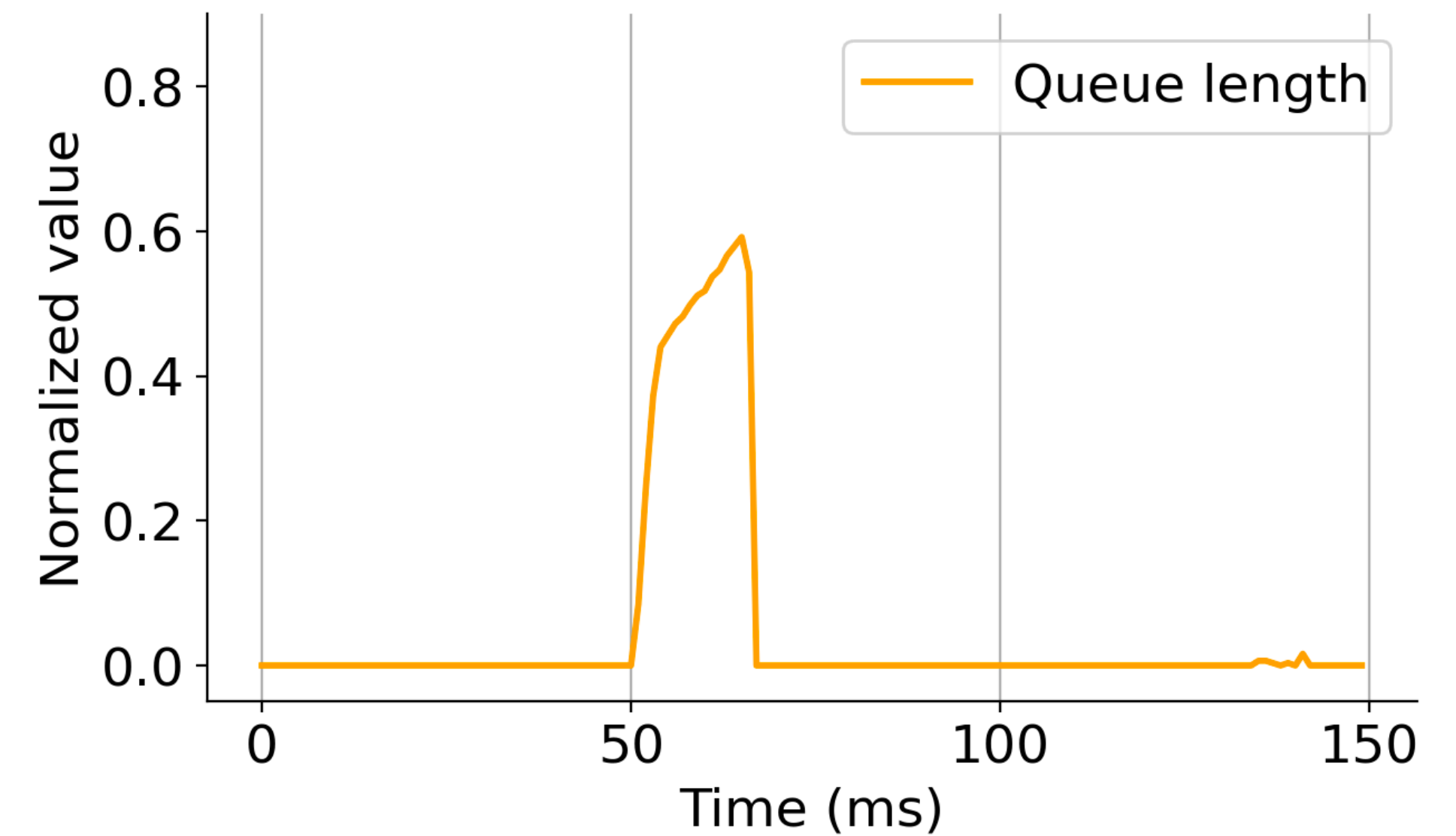
Per-port packet sent count  
with 50ms granularity



# Network telemetry imputation



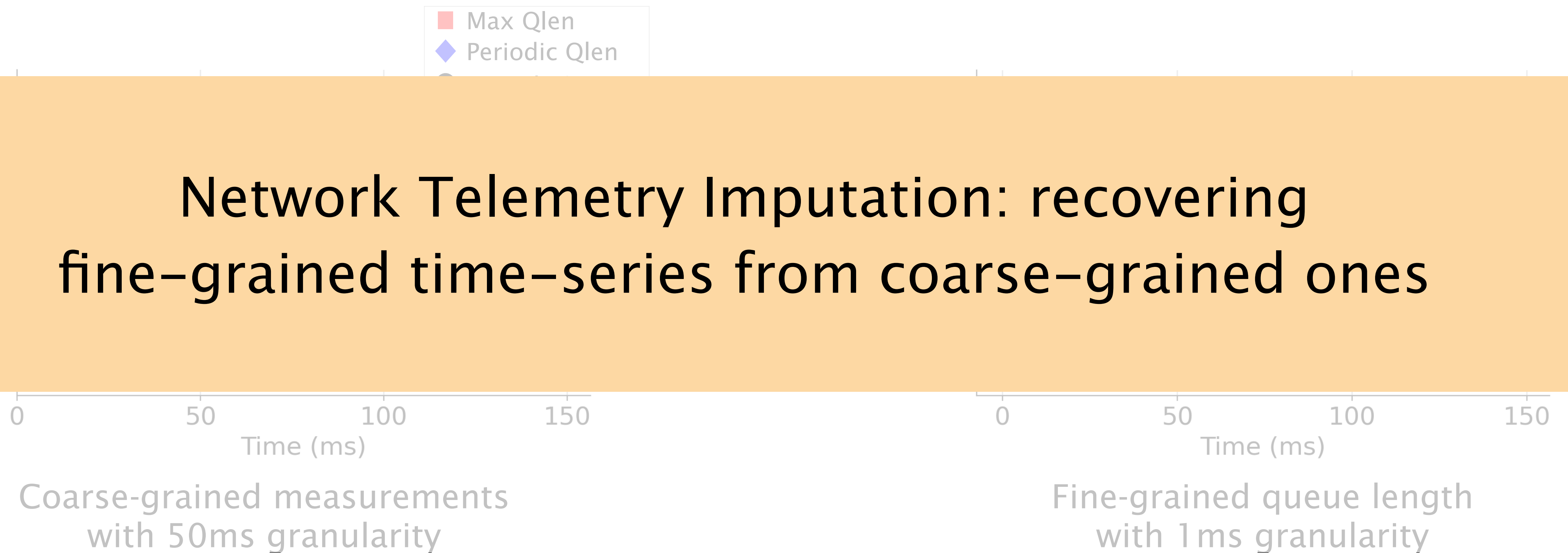
Coarse-grained measurements  
with 50ms granularity



Fine-grained queue length  
with 1ms granularity

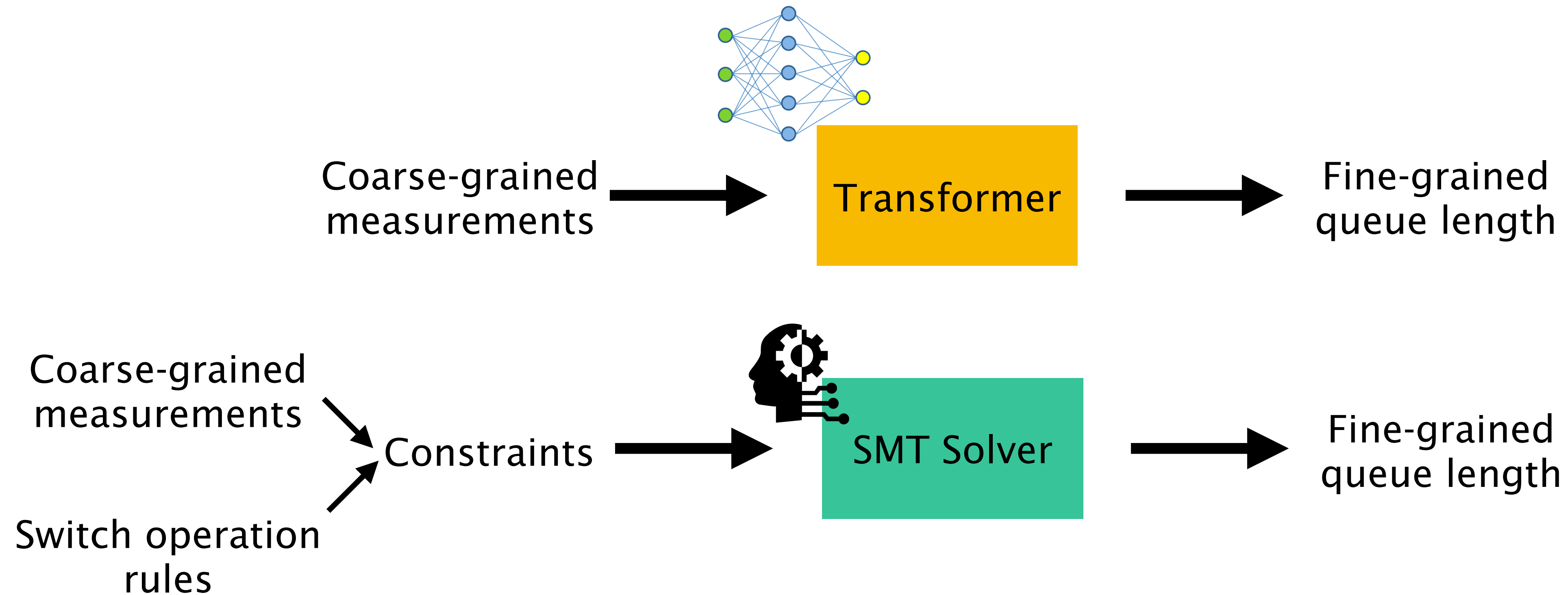


# Network Telemetry Imputation: recovering fine-grained time-series from coarse-grained ones



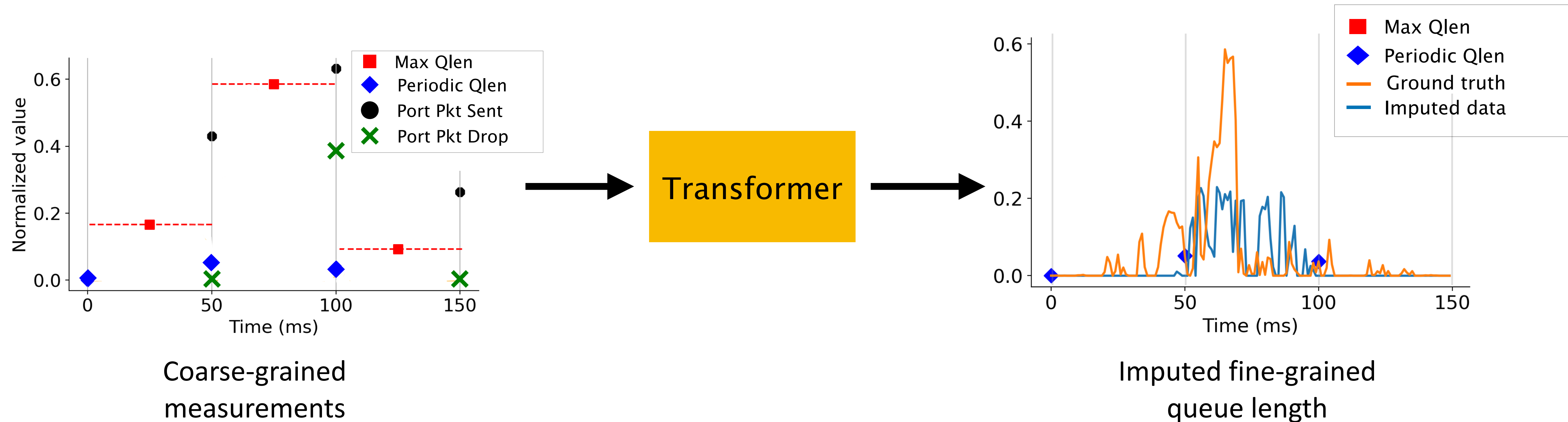


# Potential solutions: ML or Formal Methods



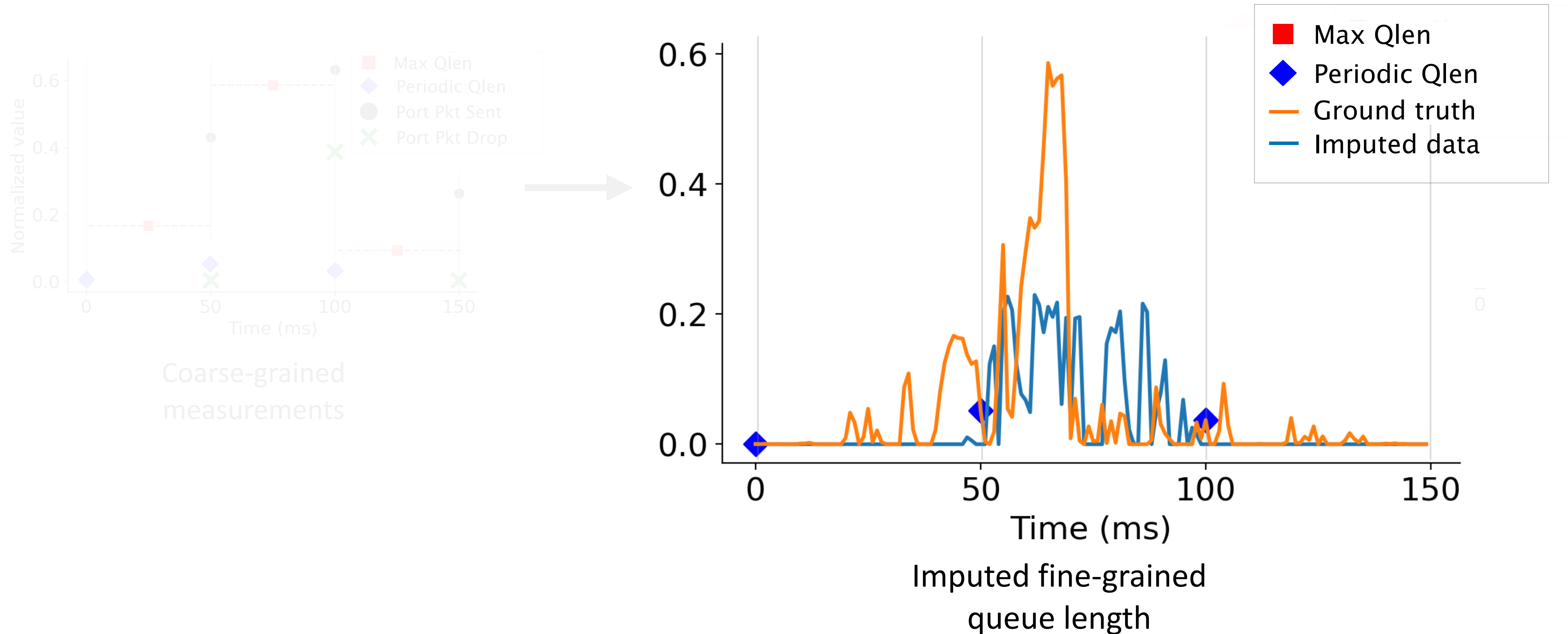


# A transformer can learn correlations, but the output lacks correctness

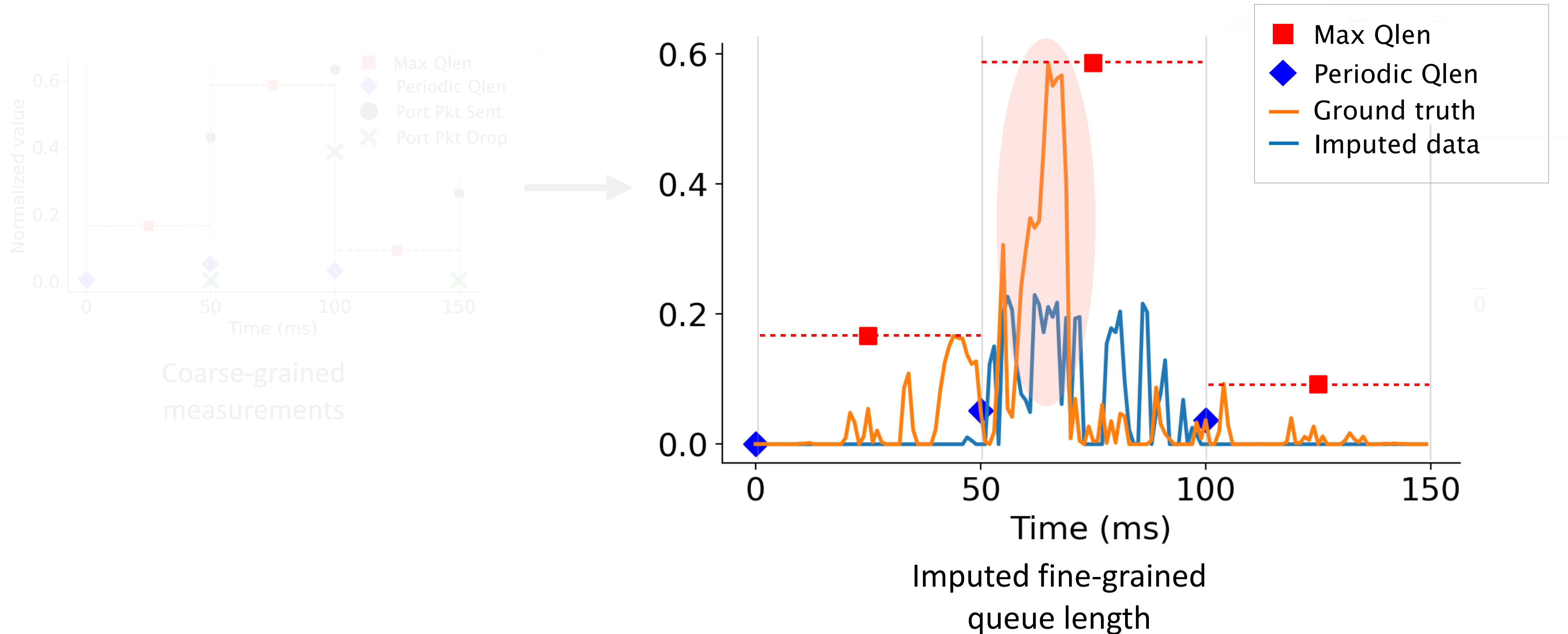




# A transformer can learn correlations, but the output lacks correctness



# 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



SMT Solver

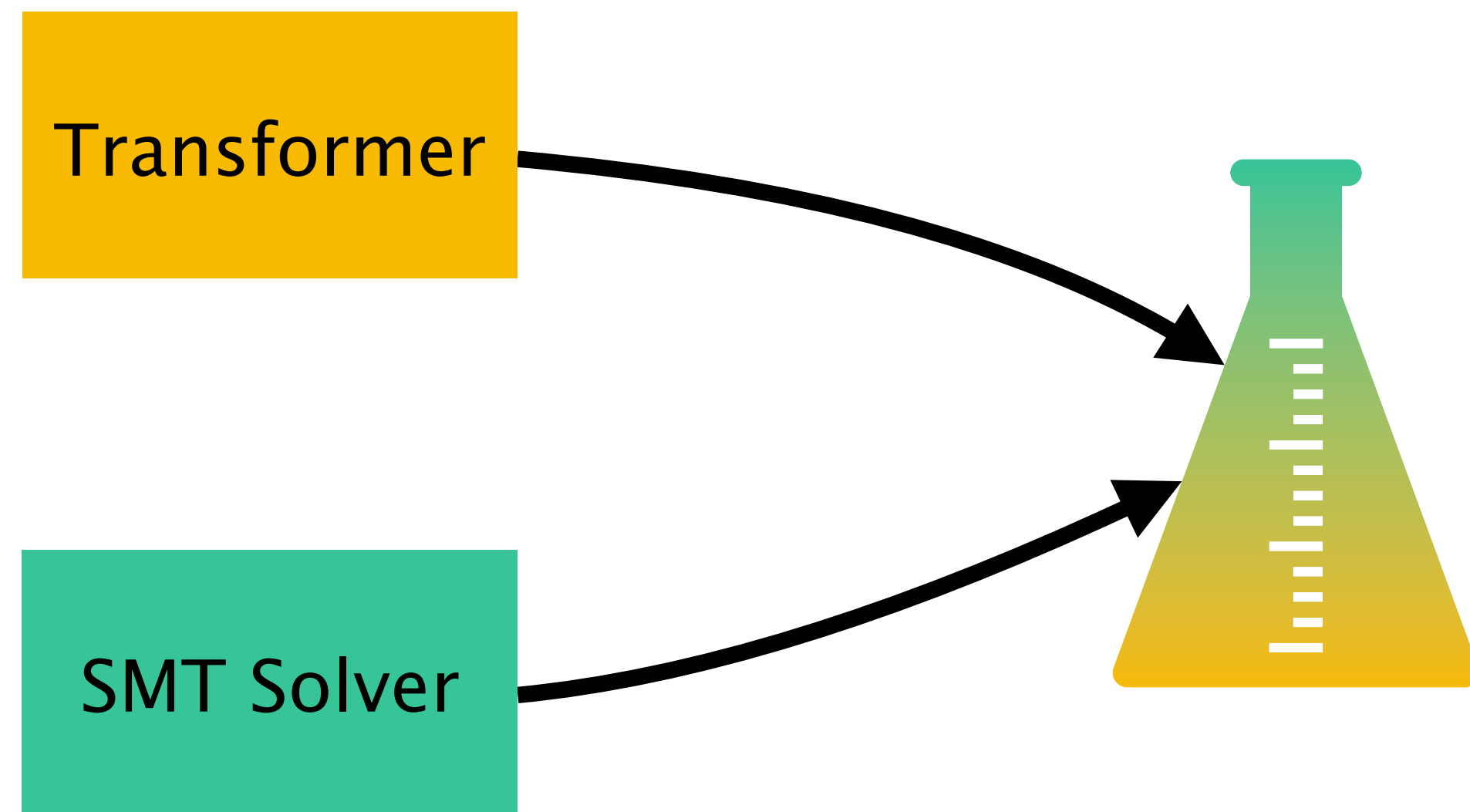
Measurement constraints:

- The maximum queue length

- The periodic queue length

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

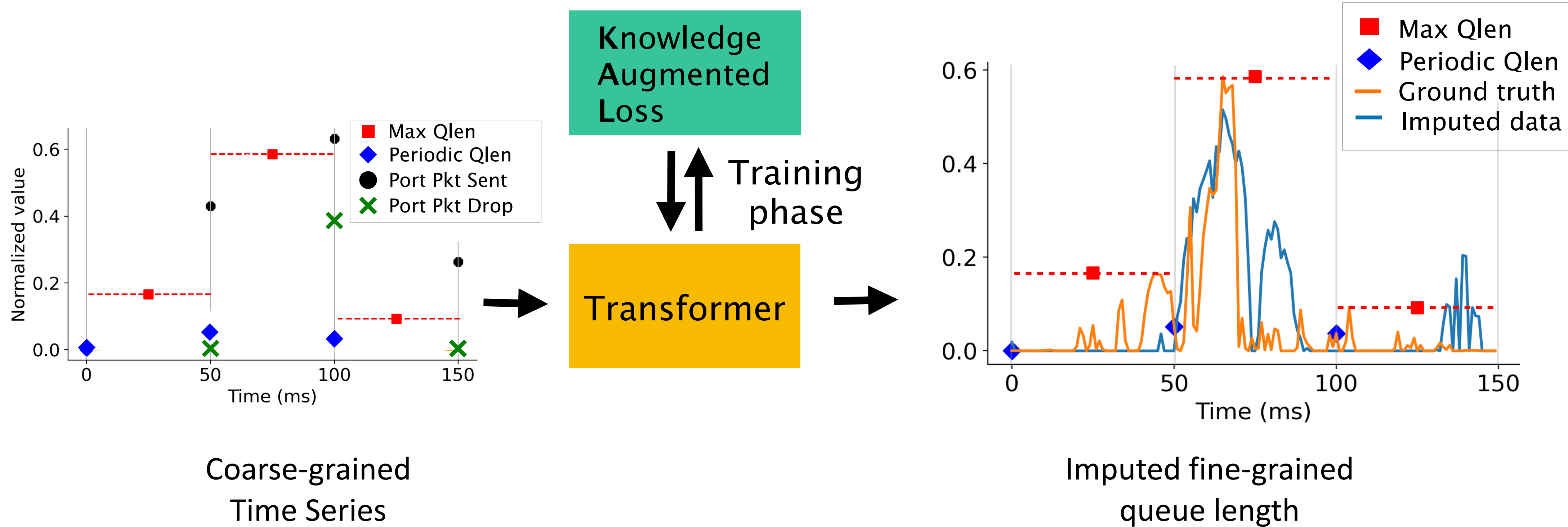


# Start from transformer



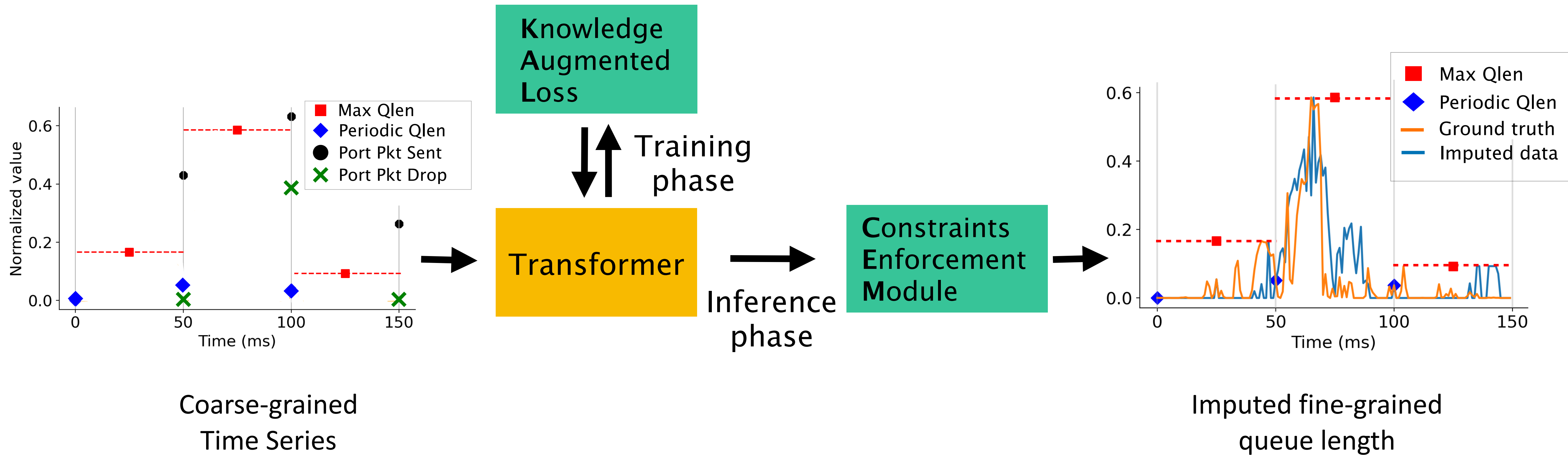
Transformer

# Knowledge augmented loss





# Constraint enforcement module



# 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?





[netsyn.princeton.edu](https://netsyn.princeton.edu)