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Communication Pattern Monitoring: Improving the Utility of Anomaly Detection for Industrial Control Systems

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Motivation

- Targeted attacks on industrial control systems (ICS) are growing in frequency and severity
  - 7,200 Internet-facing control system devices in U.S. [1]
- Industrial control systems use specialized but insecure communication protocols
  - Enterprise security tools are not able to identify zero-day attacks specific to these protocols
- **Alternative**: **anomaly-based** detection (AD) sensors
  - Natively well-suited for detecting zero-day attacks

[1] DHS ICS-CERT Monitor, October/November/December 2012

Motivation – AD Sensors

- Control systems exhibit constrained behavior:
  - Fixed topology
  - Regular communication patterns
  - Limited number of protocols
  - Simpler protocols

- Content-based anomaly detection
  - Sequence of commands, command data, request/response

- Extensible & modular framework
  - Common analysis method for different protocols

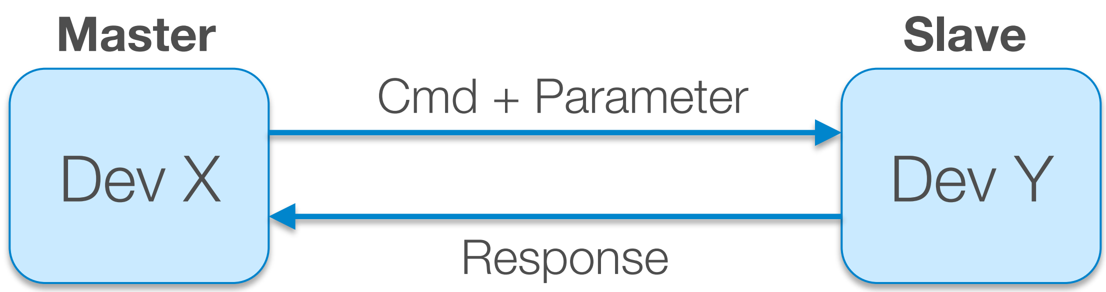
Main Contributions

- A new probabilistic-suffix-tree-based approach for ICS anomaly detection, which extracts the *normal patterns of command* and *data sequences* from ICS communications

- A false positive rate reduction mechanism, instrumental for ICS environments

- An implementation of the proposed approached applied to both real and simulated datasets

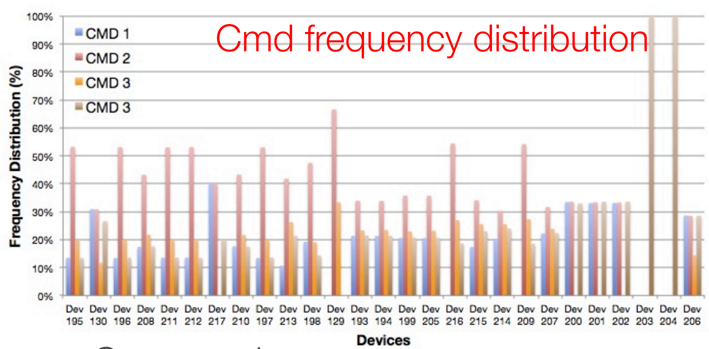
Connection Model

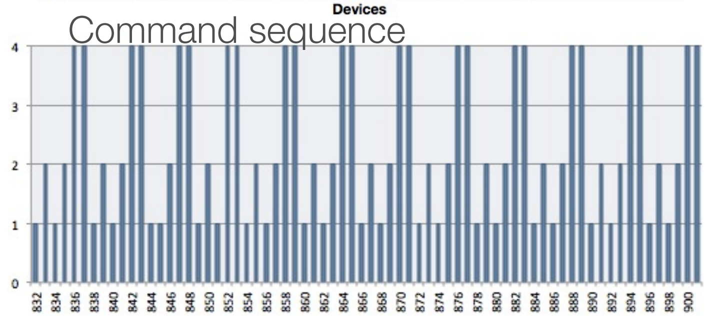


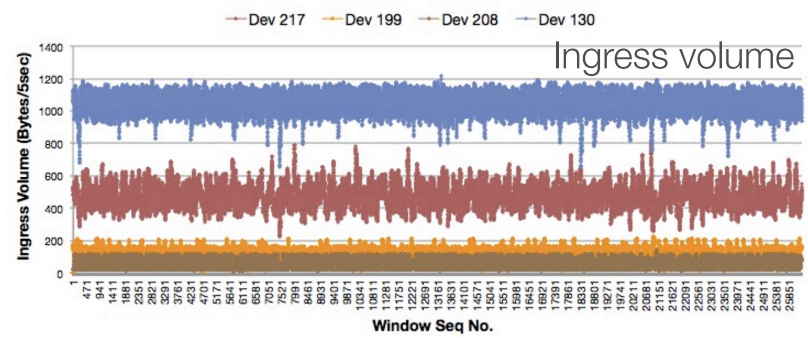
- Slave can receive N command types
- For the same command type,
  - parameters can vary, but not much
  - responses depend on the <Cmd, Parameter> pair
- Devices will have an ‘internal’ state
  - May not be directly visible
  - Operational modes, normal/compromised

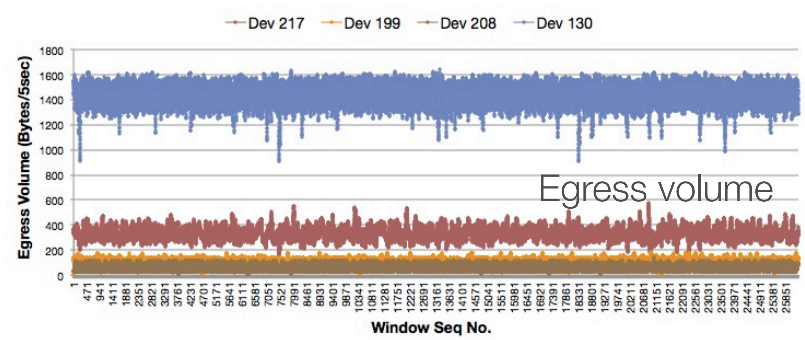
Predictable Behavior of ICS Network

- Globally?
  - No. Devices behavior change with different frequencies.
- Device level?
  - Better, but still not deterministic as a device may communicate with many devices
- Connection level?
  - Stable, deterministic!



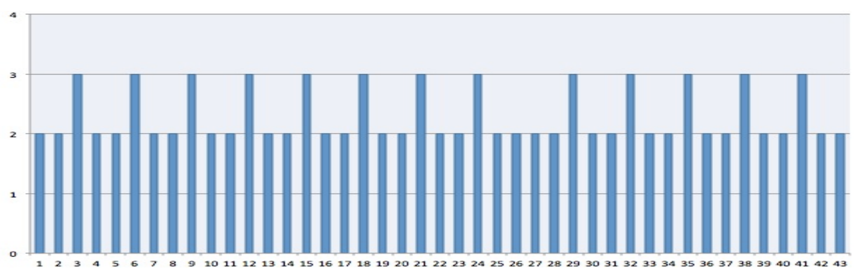


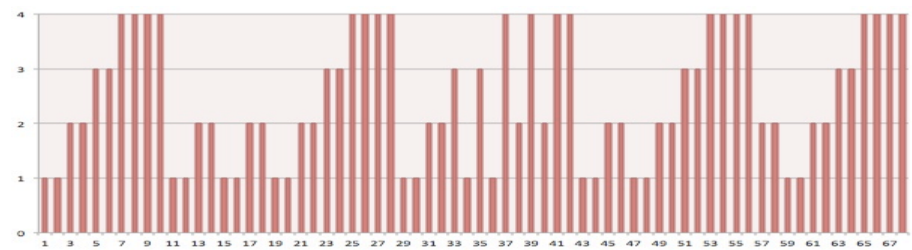




Patterns for Commands and Data

- Given a connection, the sequence of commands has patterns
  - Periodic operations -> form a transaction of commands





- Given a command type over a connection, data is mostly either
  - a fixed value or
  - a value changing with a pattern

- Both can be modeled as sequence patterns

9c410001
9c420001
9c430001
9c440001
9c450001
9c460001
9c470001
9c480001
9c490001
9c4a0001
9c4b0001
9c4c0001
9c410001
9c420001
9c430001
9c440001
9c450001

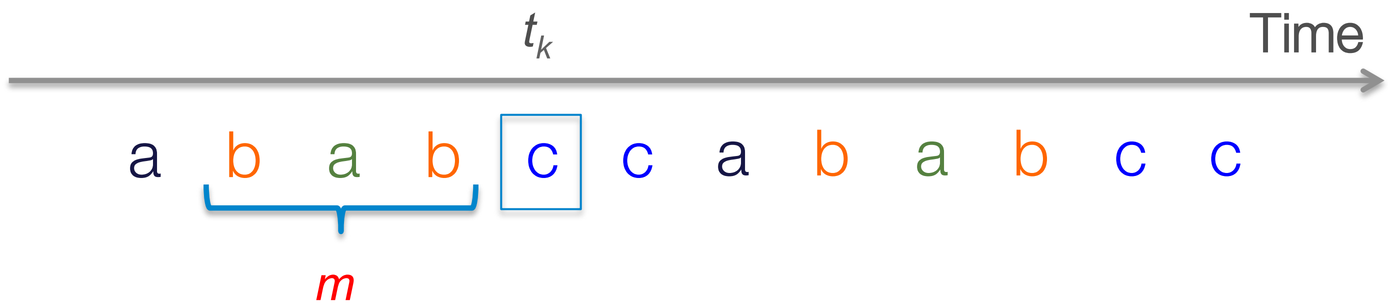
Patterns for Commands and Data

- Given a connection, the sequence of commands has patterns
  - A transaction of commands (operations) -> a pattern of commands
- Given a command type over a connection, data is mostly either
  - a fixed value or
  - a value changing with a pattern
- Both can be modeled as sequence patterns

We detect anomalies in command and data sequences

- Master sends unknown commands
  - with normal/abnormal data
- Master sends known but abnormal commands
  - out of context
- Slave responds with abnormal response data
- Master sends requests to unusual slaves
  - that it has never/rarely communicated with

How to Model Sequence Patterns?



- What is the probability of seeing a certain command at time t_k given a history of commands of length m?

Learning Patterns of Commands and Data

- Learning the normal sequence of commands = Learning a Markov chain of order *m*

- Challenges
  - Packets can be missing
  - Patterns may vary

- Need for a probabilistic approach
  - Learn the conditional probability distribution (CPD)

$$Pr(\sigma_t | \sigma_{t-m} \cdots \sigma_{t-1})$$

Learning Patterns Using PST

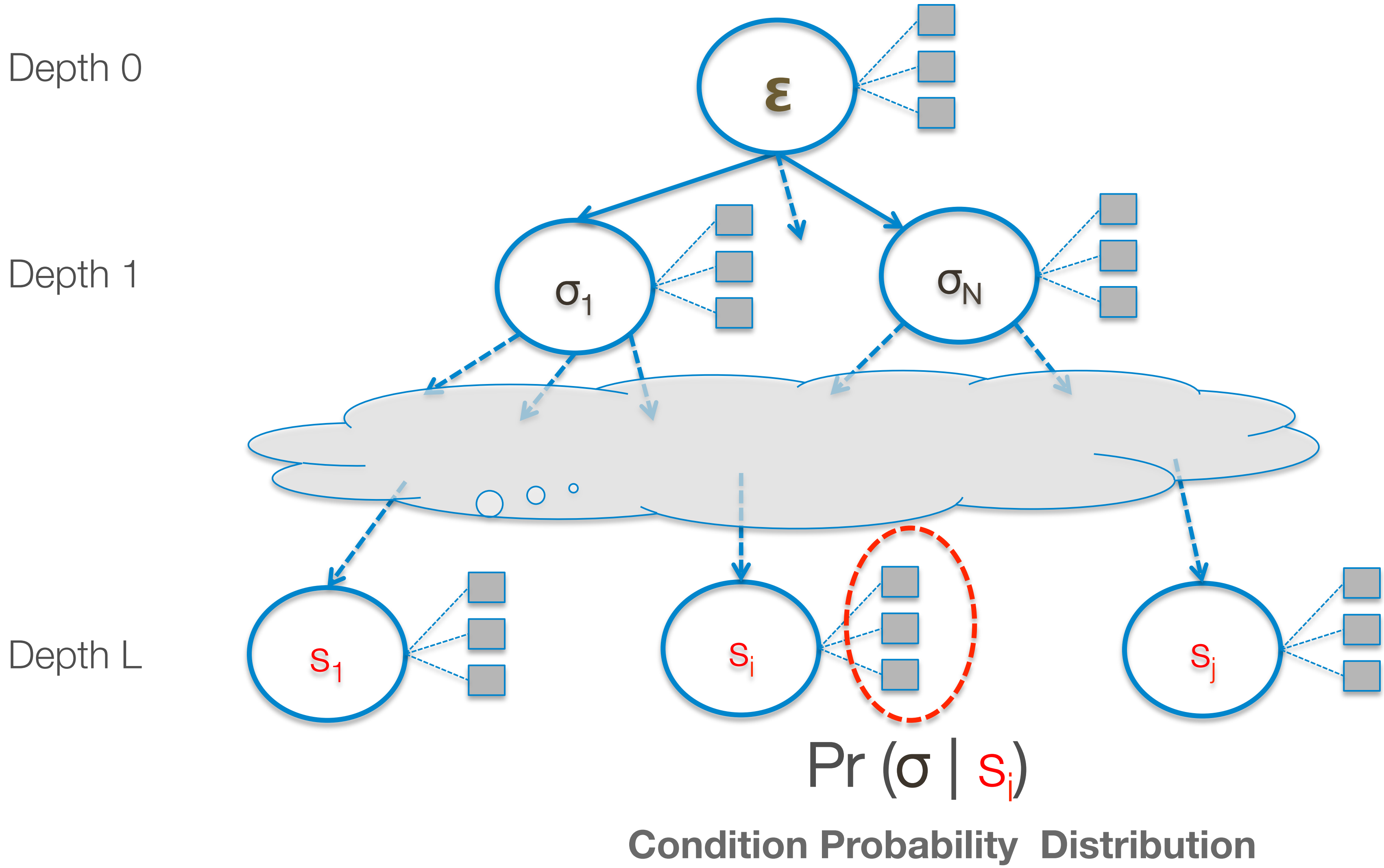
- Probabilistic Suffix Tree (PST)
  - A variable-order Markov model
  - Bounded depth (the maximum order), *L*

$$Pr(\sigma_t | \sigma_1 \sigma_2 \cdots \sigma_{t-1}) \sim Pr(\sigma_t | \sigma_{t-k} \cdots \sigma_{t-1})$$

, where k <= L

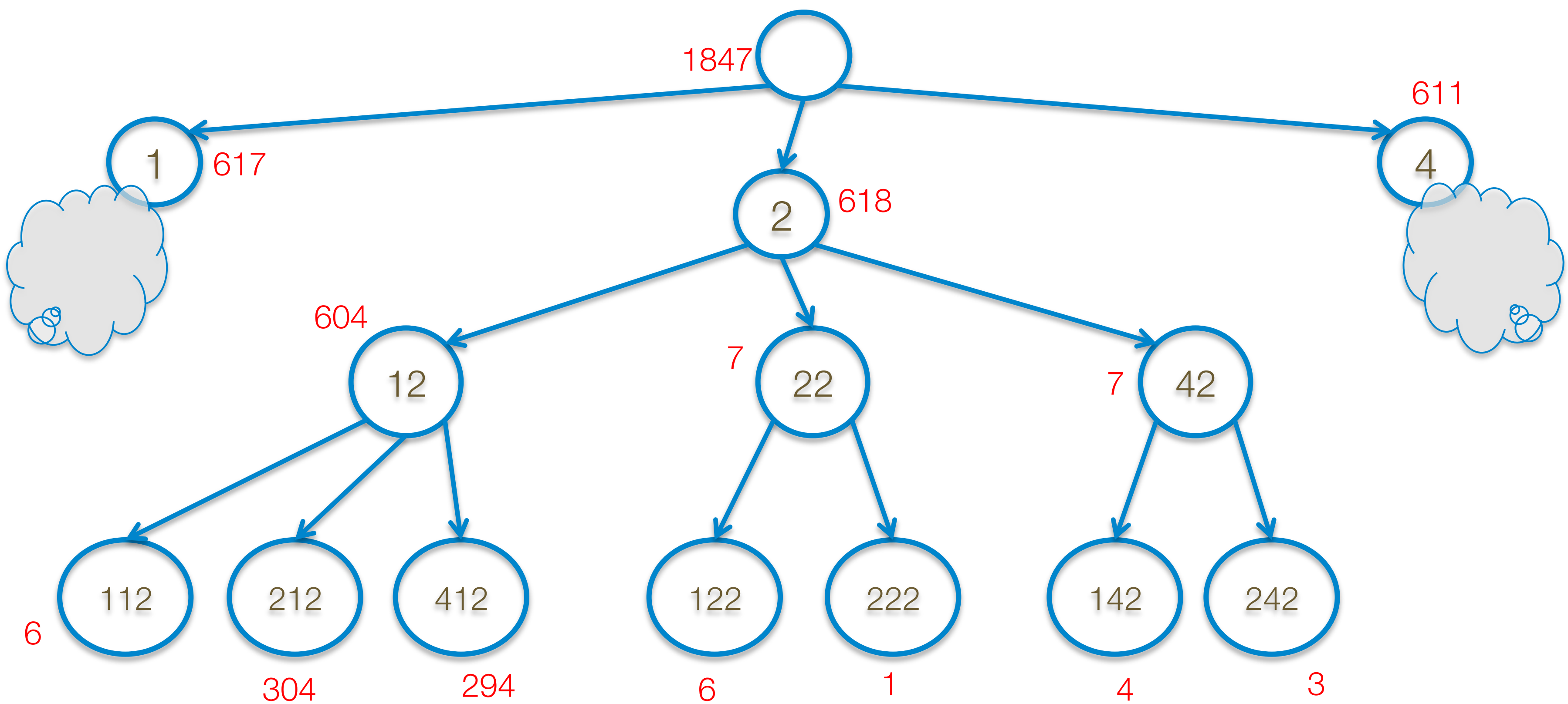
  - Efficiently represents CPD using tree structure

PST Structure



PST Example

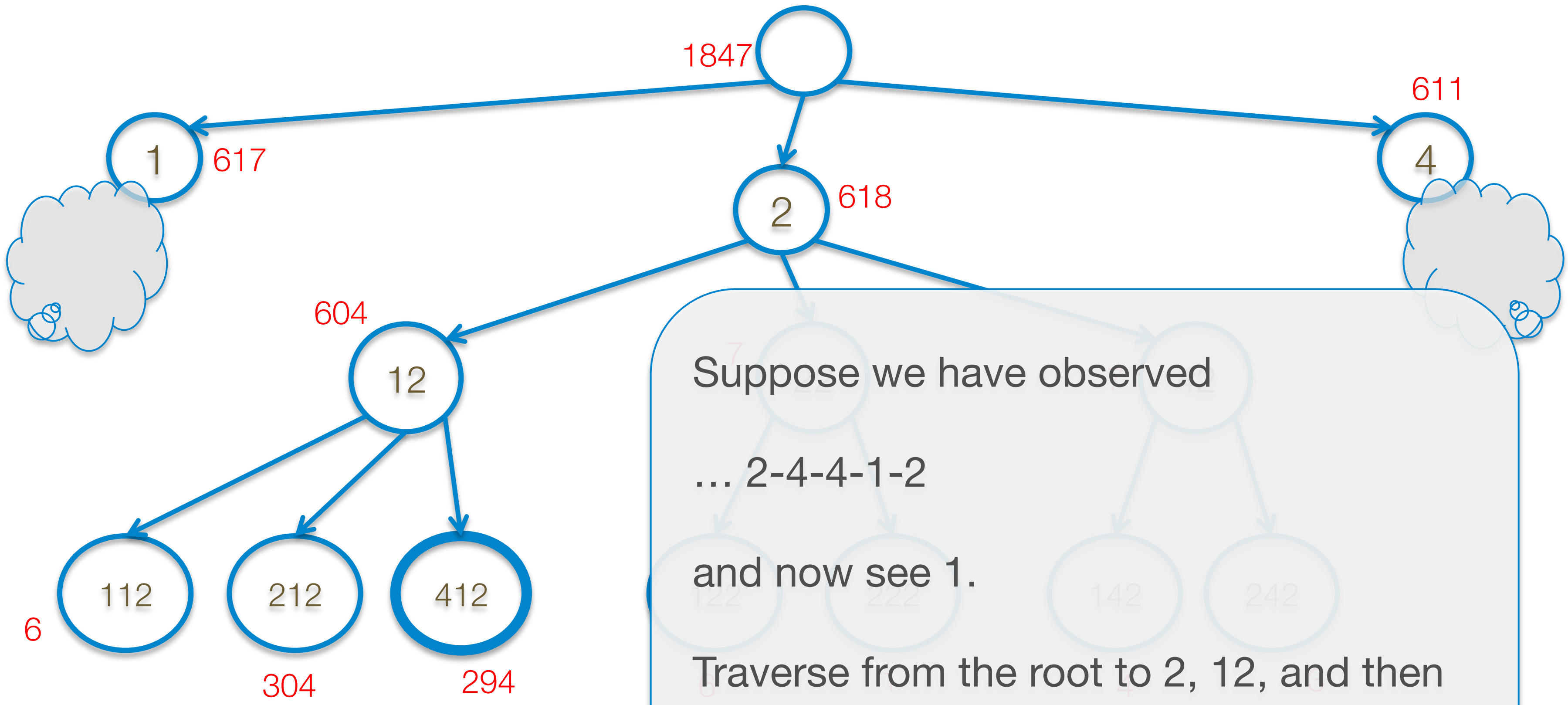
Base pattern: 1 2 1 2 4 4 L (MaxDepth) = 3



Likelihood Calculation

Base pattern: 1 2 1 2 4 4

L (MaxDepth) = 3



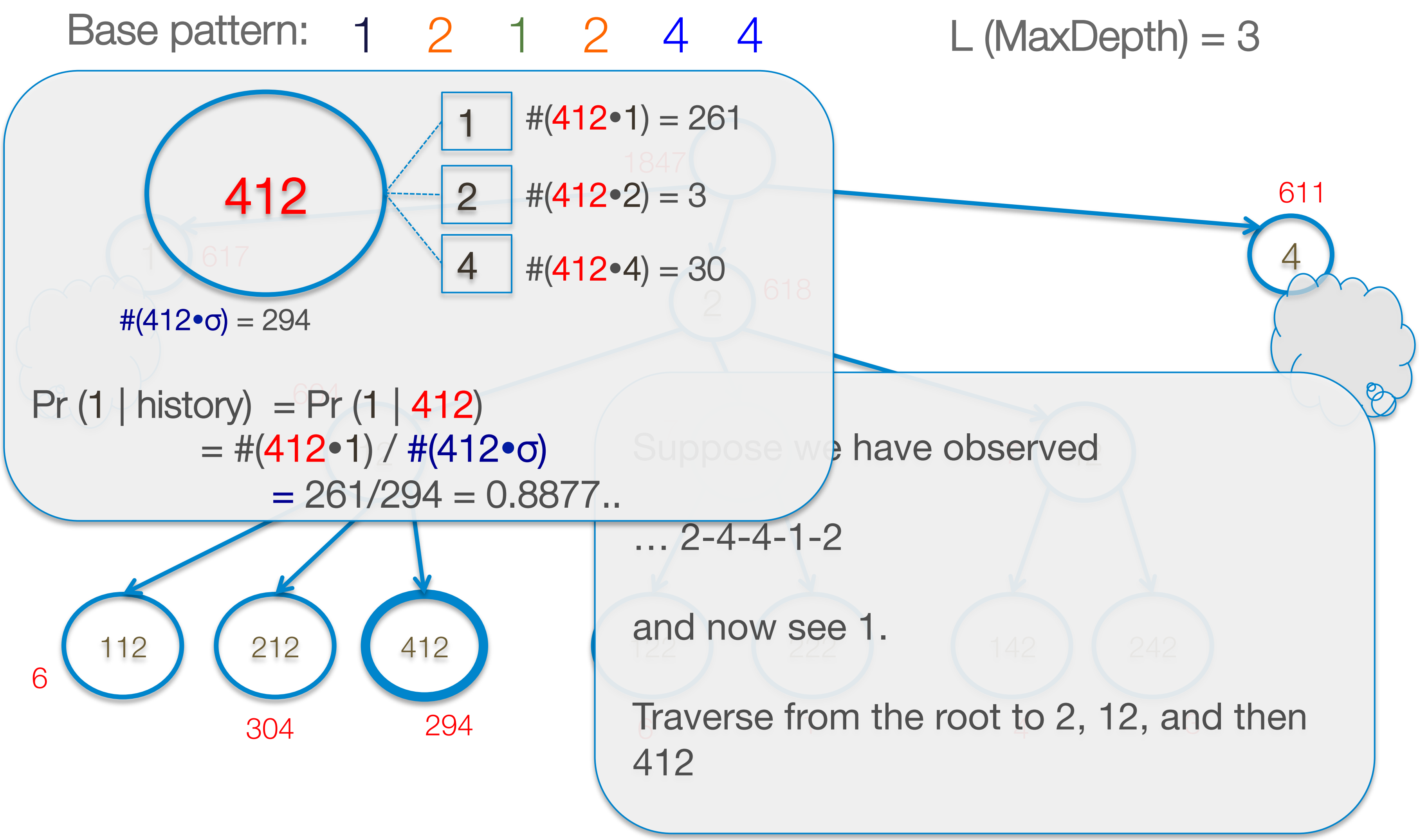
Suppose we have observed

... 2-4-4-1-2

and now see 1.

Traverse from the root to 2, 12, and then 412

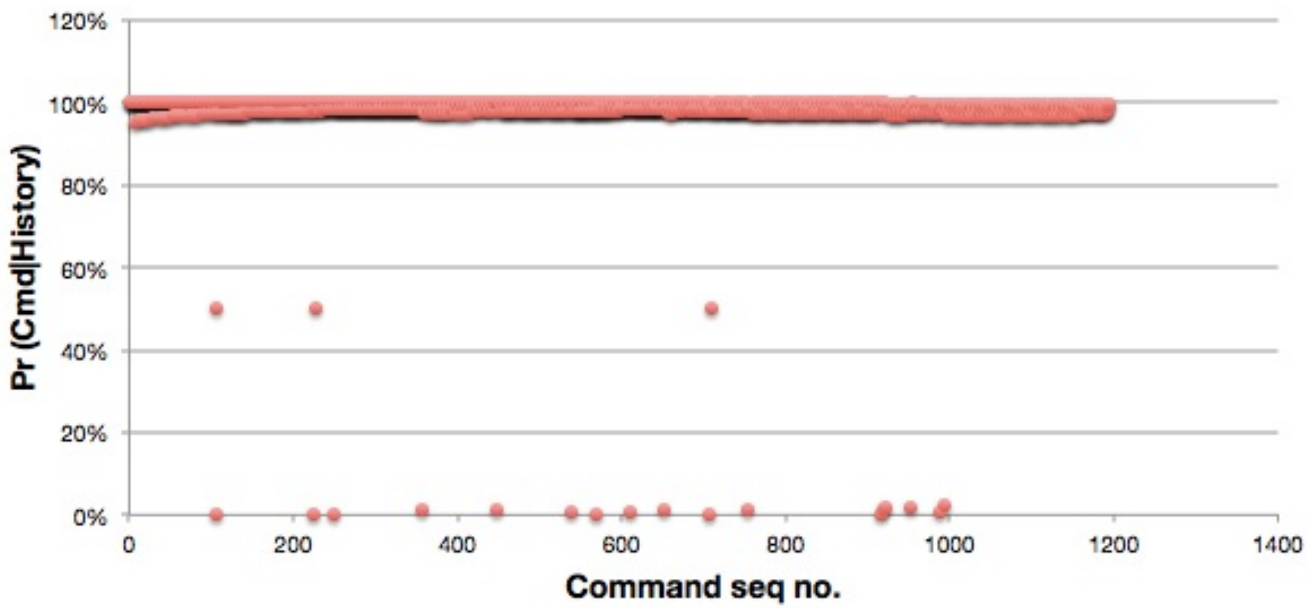
Likelihood Calculation



Incremental PST

- For online learning
  - Batch learning is not applicable to network-level AD due to the flow of packets
  - Need to be able to deal with varying patterns
- Update the tree whenever reading an element, **σ**
  - Start from an empty tree
  - Keep recently-read elements
  - Update the counts $\#(s \bullet \sigma)$ for recent history s of length 1,…, L

Incremental PST Example



- A MODBUS connection
  - Base pattern: 1-2-1-2-4-4
  - Normal sequence
  - Mostly, the likelihoods are close to 1.0
  - Sometimes, near zero -> because of missing packets!

False Positive Due to Missing Packets

Base pattern: 1 2 1 2 4 4 L (MaxDepth) = 3

1-2-1-2-4-4 - 1-2-2-4 - 1 Time

Pr(2|4-1-2) = 1.69%

- Missing one packet can cause multiple false positives
  - In the example, missing '1' causes two false positives
- We want low false positive rate!

Incremental PST with Prediction

- If $Pr(\sigma_t|\sigma_{t-L}\cdots\sigma_{t-1}) < \theta$
  - assume an element is missing and try to restore it!

- First, find what we should have seen.

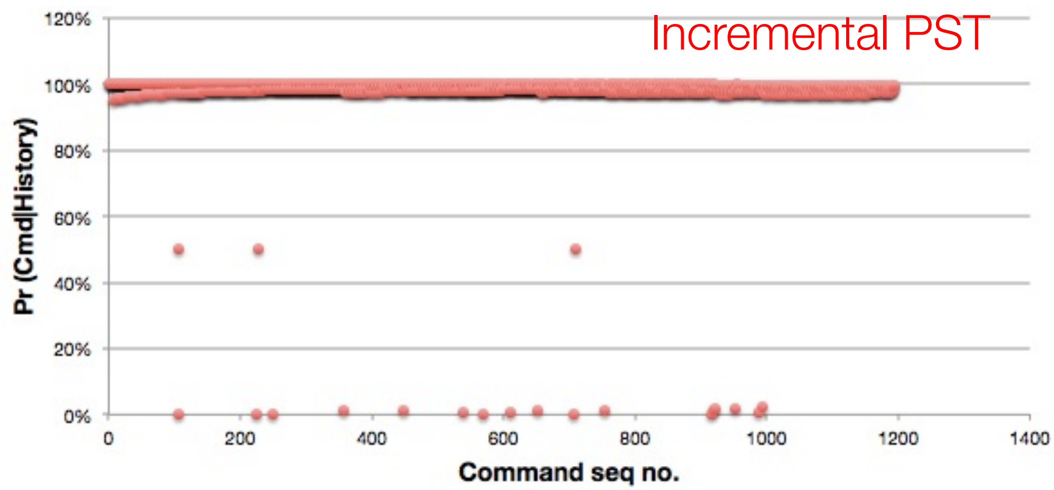
$$\sigma_{ML} = \arg\max_{\sigma} Pr(\sigma|\sigma_{t-L}\cdots\sigma_{t-1})$$

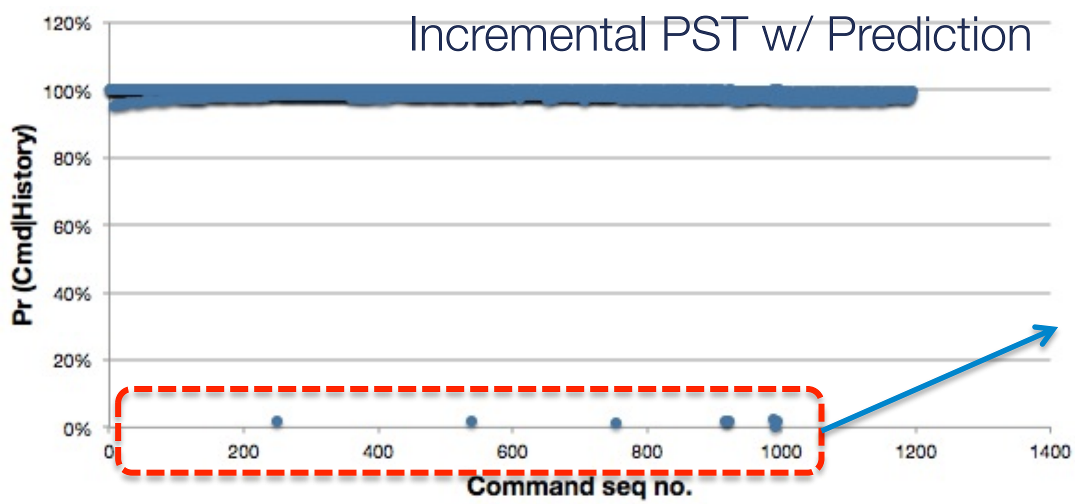
- Then, use it to calculate the new likelihood

$$\cancel{\sigma_{t-L}}\sigma_{t-L+1}\cdots\sigma_{t-1} \longrightarrow \underbrace{\sigma_{t-L+1}\cdots\sigma_{t-1}\sigma_{ML}}_{\text{Length = L}}$$

$$\boxed{\begin{aligned}&Pr(\sigma_t|\sigma_{t-L}\cdots\sigma_{t-1})\\&\quad\sim Pr(\sigma_{ML}|\sigma_{t-L}\cdots\sigma_{t-1})\cdot Pr(\sigma_t|\sigma_{t-L+1}\cdots\sigma_{t-1}\sigma_{ML})\end{aligned}}$$

Incremental PST with Prediction Example





Reduced many FP!
But, still, some are FP.

4-4-1-2-4

1-2-1-2-1-4

1-2-1-2-1-2

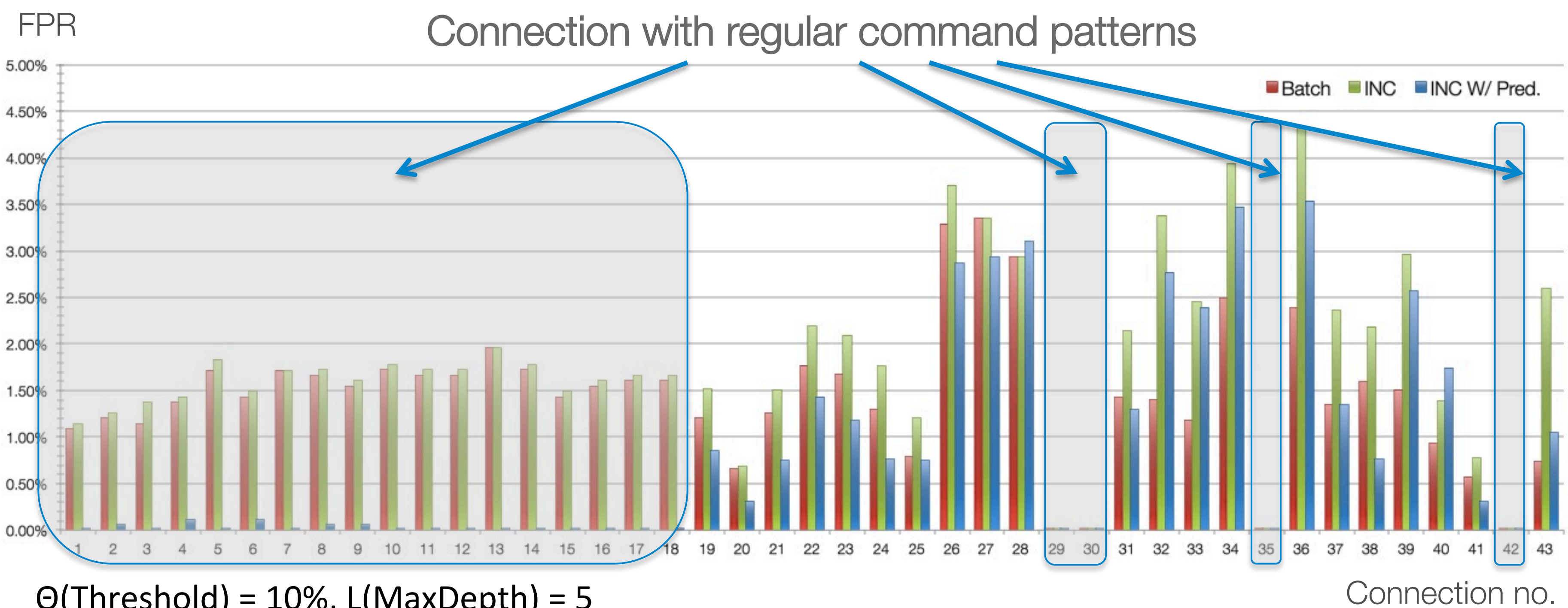
It doesn't restore well when consecutive packets are missing!

Evaluation

- Modbus traffic
  - 2 masters, 25 slaves
  - 86 connections (43 pairs)
  - 4 cmd types
  - No attack/anomaly is known
  - Some packets are missing

- Synthetic data (random sequences of commands)
  - Evaluate the detection rate and the false positive rate

False Positive Rates of Modbus Traffic



Θ(Threshold) = 10%, L(MaxDepth) = 5

Likelihood

$$FPR = \frac{\sum_{t=1}^{N} I\Big(\overbrace{Pr(\sigma_t|\sigma_1 \cdots \sigma_{t-1})} < \theta)\Big)}{N}$$

$I(true) = 1$

Sequence length

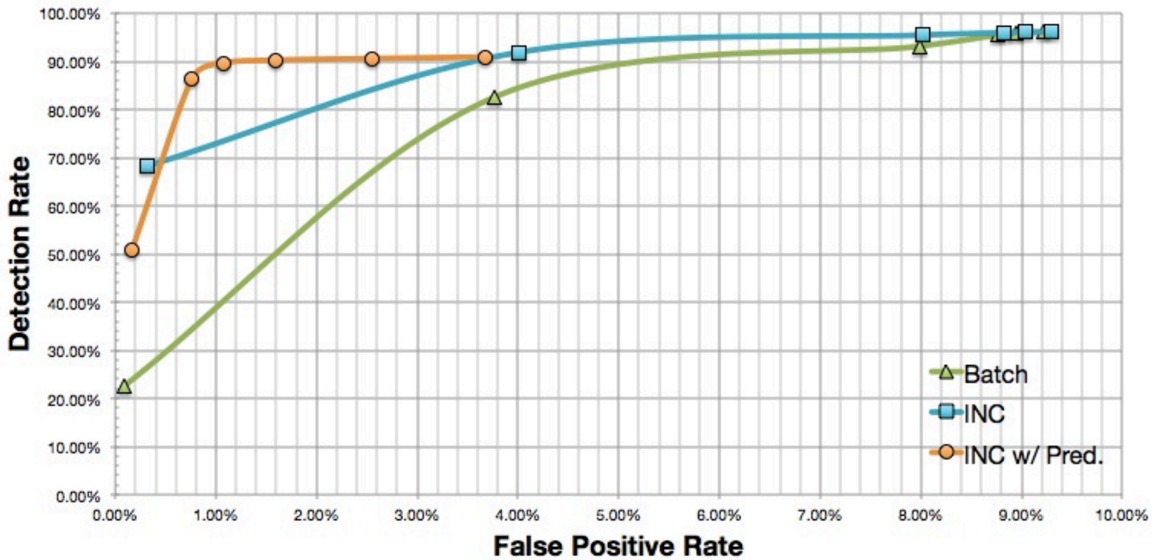
Generation of Random Sequence of Commands

- Generate a random base pattern

- Then, generate a random sequence based on the pattern
  - With a missing probability, a command can be dropped
  - With an attack probability, a random short sequence is inserted

- Input parameters
  - Min, max of base pattern length
  - # of command types
  - Missing, attack probabilities

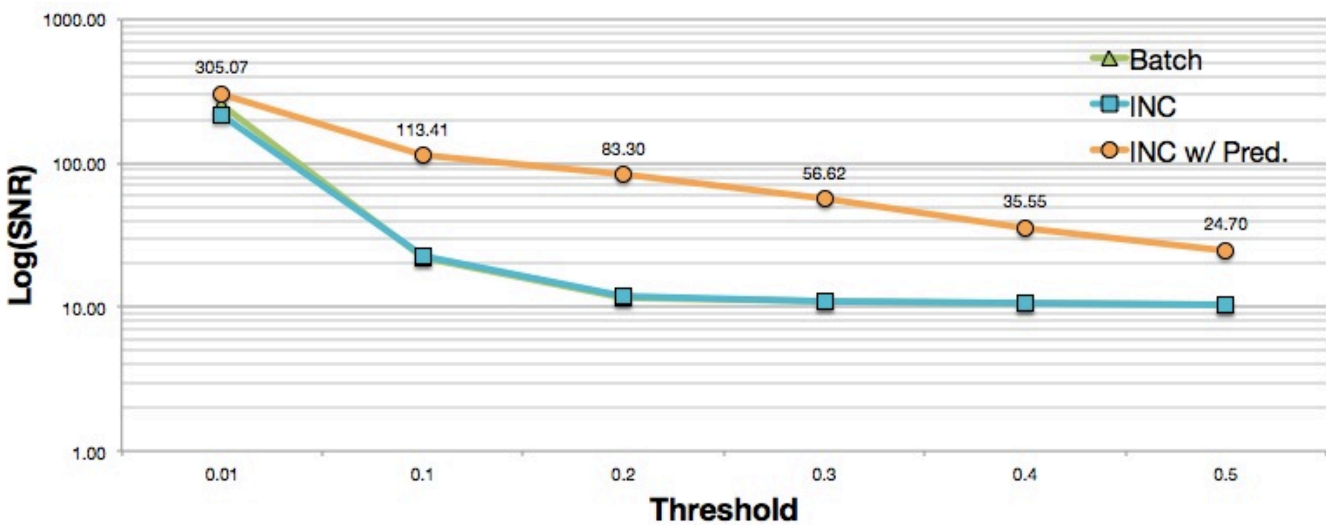
Better Performance for INC w/Pred



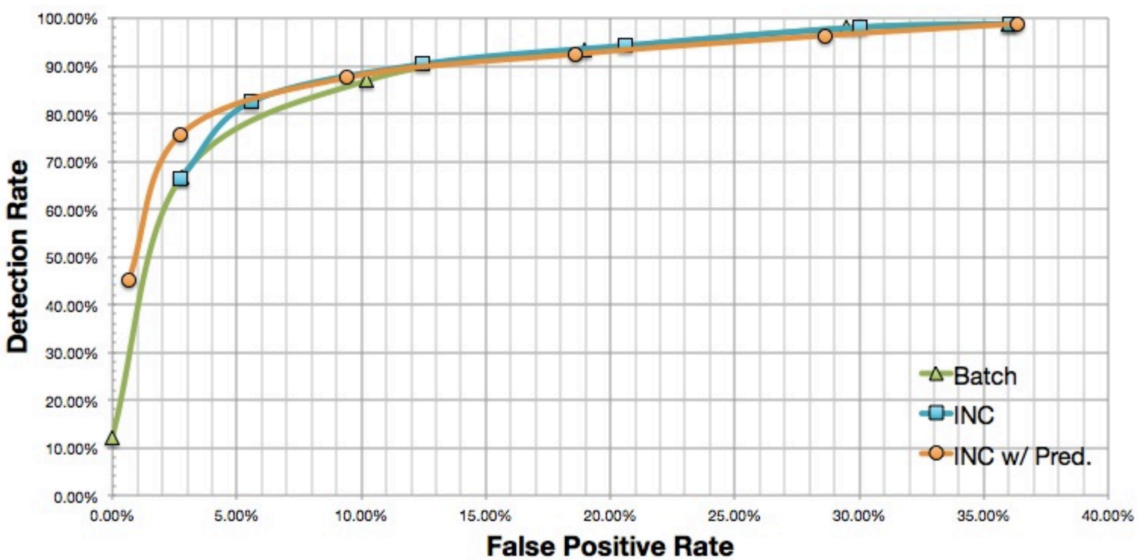
ROC curve

Miss prob = 10%
MaxDepth(L) = 5

Signal-Noise Ratio



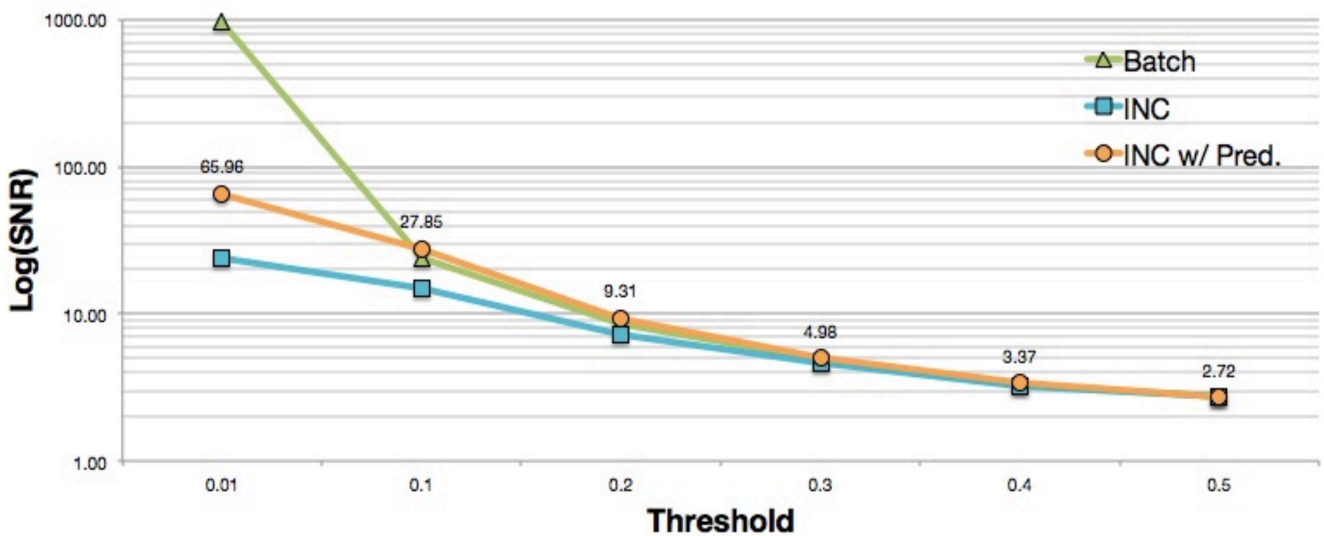
Similar Performance Across All Methods



ROC curve

Miss prob = 50%
MaxDepth(L) = 5

Signal-Noise Ratio



Conclusions

- We proposed a novel anomaly detection method for ICS devices
  - Built accurate models
  - Reduced false positive rate
- The proposed method has been implemented and applied to a Modbus network testbed and a synthetic dataset
  - Reached a high detection rate for the synthetic dataset while successfully keeping the false positive rate in check

Future Work

- A complete evaluation on real operational datasets will be a critical next step
  - We are currently analyzing real Modbus traffic
- We plan to extend the set of protocols that we investigate and to target different industry sectors
- We plan to also extend the ICS-specific anomaly detection techniques within a more flexible and general framework, that can cope with long lasting attacks targeting our architecture

Thank you!

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