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Design of Policy Engine to Prevent Malware Propagation in Advanced Metering Infrastructure

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Introduction

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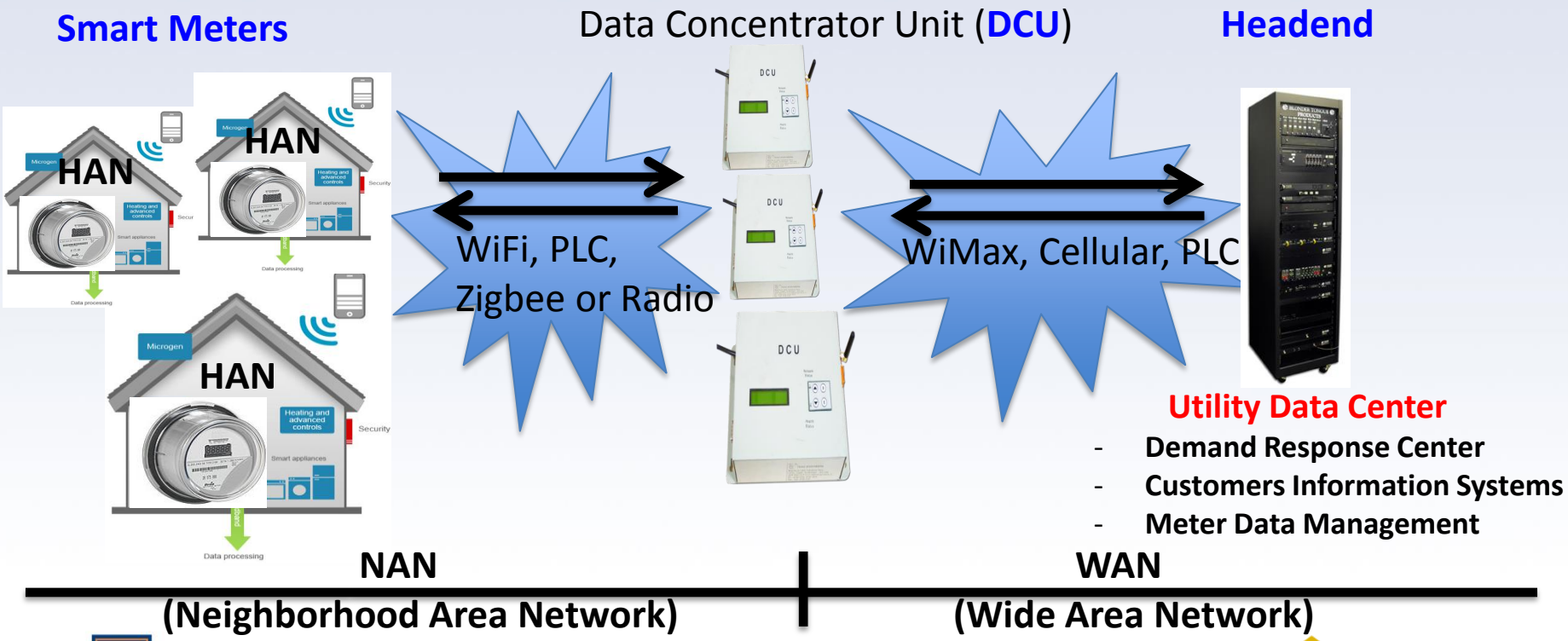
Introduction

- Advanced Metering Infrastructure (AMI)



Introduction

- Goals of Advanced Metering Infrastructure (AMI)
  - Reliability
    - Smart metering
    - Automated real-time monitoring
  - Efficiency
    - Demand response and control
    - Active energy management
    - Remote connect/disconnect
  - Security
    - Improved by monitoring and reliability

Cyber Attacks in AMI

- Network availability attack
  - Overwhelm the communication and computational resources
- Data attacks
  - Insert, alter or delete data in the network traffic
- Privacy attacks
  - Learn users' private information by analyzing electricity usage data
- Device attacks
  - Compromised or control a device

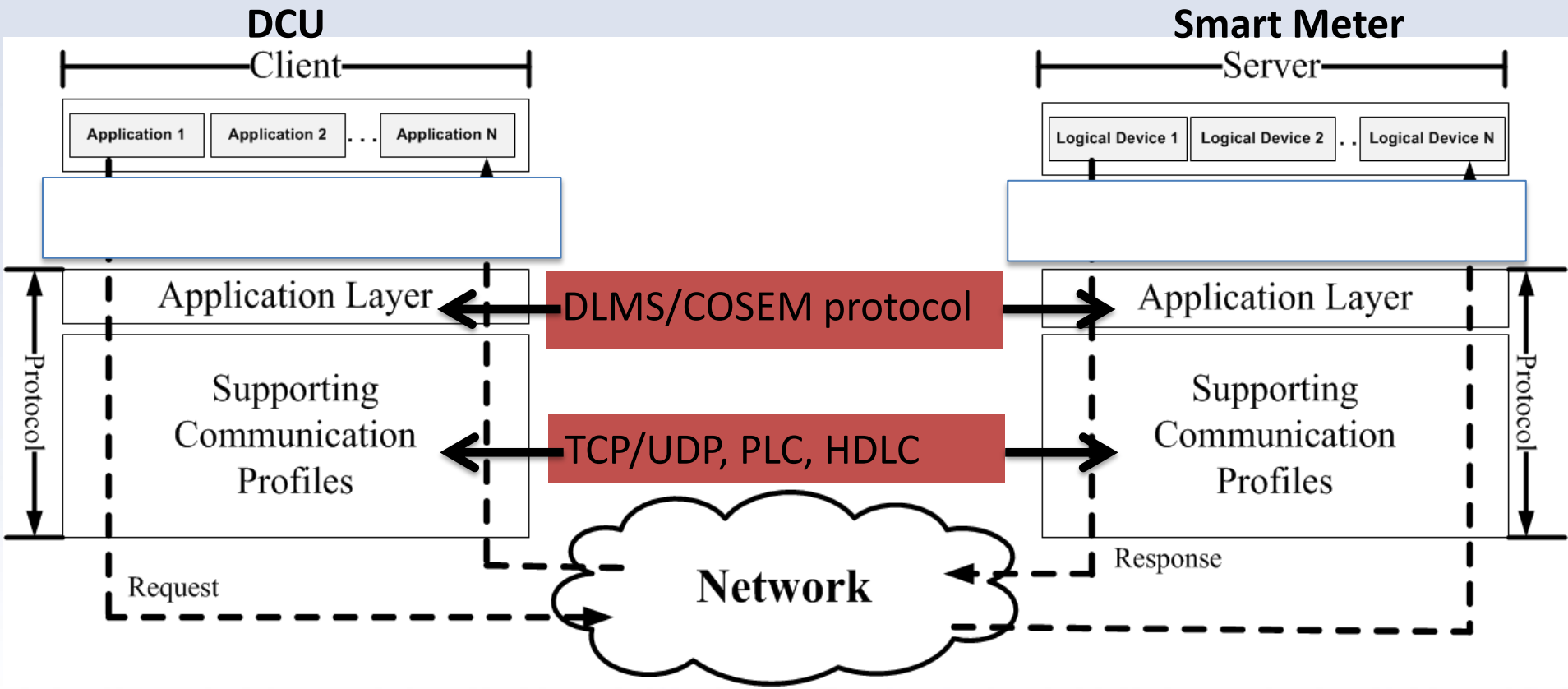
Cyber Attacks in AMI

- Malware (Malicious Software)
  - Stuxnet, Auora worm in industrial systems
  - Warning from Blackhat, McAfee
  - Control systems and disrupt operations
  - Launch malicious commands
    - Blackout, remote disconnects
  - Infect other systems in AMI

Policy Engine

- What is Policy Engine?
  - A set of policy rules
  - Detection/Prevention of Malware carried by an application layer protocol
    - Malware propagation during communications
  - Monitor bi-directional communications
    - Client request (DCU, Headend)
    - Server response (Smart meters)

Policy Engine



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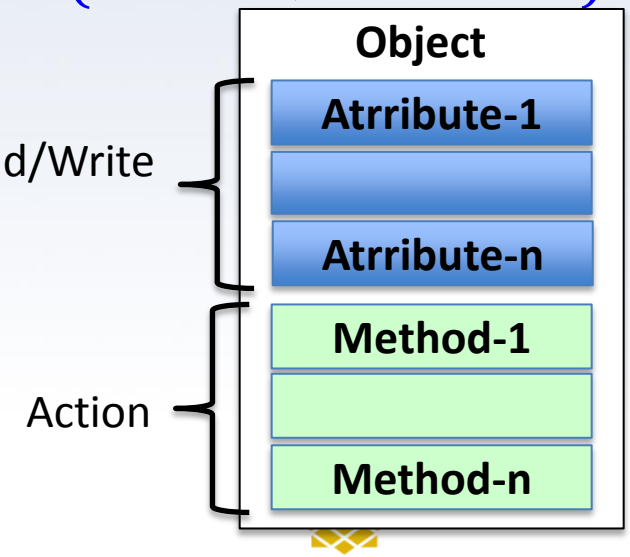
DLMS/COSEM Protocol

- An standard application protocol for AMI
- DLMS (Device Language Message Specification)
  - define objects found in meters
- COSEM (Companion Specification for Energy Metering)
  - Define communication between meters and devices needing meter information

DLMS/COSEM Protocol

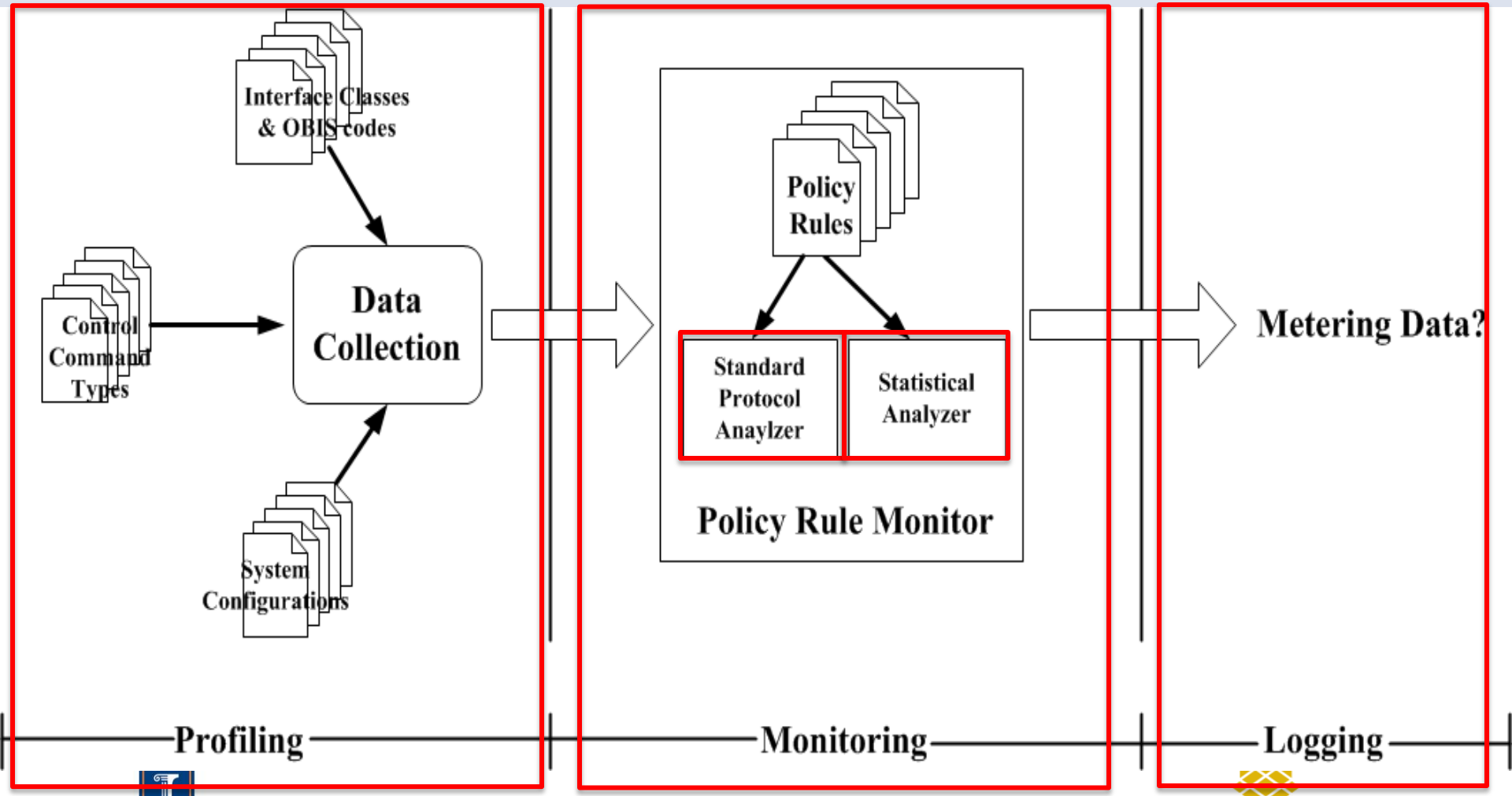
- Interface classes (Class ID)
  - All meter data as objects
  - Object Identification system (OBIS)
    - OBIS code is called a logical name (1st attribute value)
    - [EX] Reading energy value
      - **Register (class_id : 3)**
      - **Obis code is "1.1.1.8.0.255"**
      - Reading second attribute value
  - 70 standard interface classes



Motivation for Policy Engine

- Compromised applications or devices
- Propagate malware by hiding itself into DLMS/COSEM traffic
  - Violation of Packet formats
    - Specification of DLMS/COSEM application layer
  - No metering data
  - Containing malware features

System Architecture of Policy Engine



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System Architecture of Policy Engine

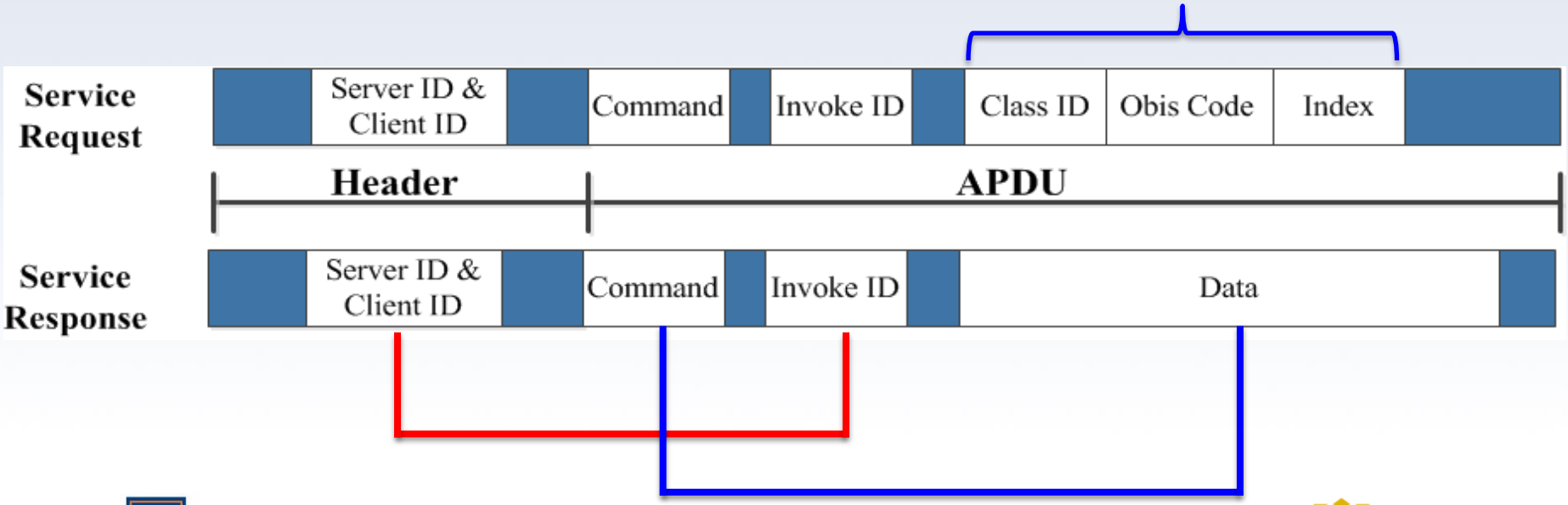
- Data collection system
  - OBIS, Command types, system configurations
- Policy Rule Monitoring system
  - Policy rules from the standard protocol
  - Policy rules from two statistical features
- Logging system
  - Recording malicious data

Standard Protocol Analysis

- DLMS/COSEM protocol
  - It creates application data
    - APDU (application protocol data unit)
  - Policy rules
    - Syntactic policy rules
    - Semantic policy rules
    - Access policy rules
    - Communication policy rules

Standard Protocol Analysis

- DLMS/COSEM Protocol
  - Syntactic/Semantic/Access/Communications
    - Malware overwrite the APDU



Statistical Analysis

- Two features of malware
  - Packed or encrypted binaries are around 90%
  - Executable format
- Smart meters
  - Low-computational power
  - Limited bandwidth and resourses
- Statistical analysis tools
  - Entropy analysis
  - N-gram analysis

Statistical Analysis

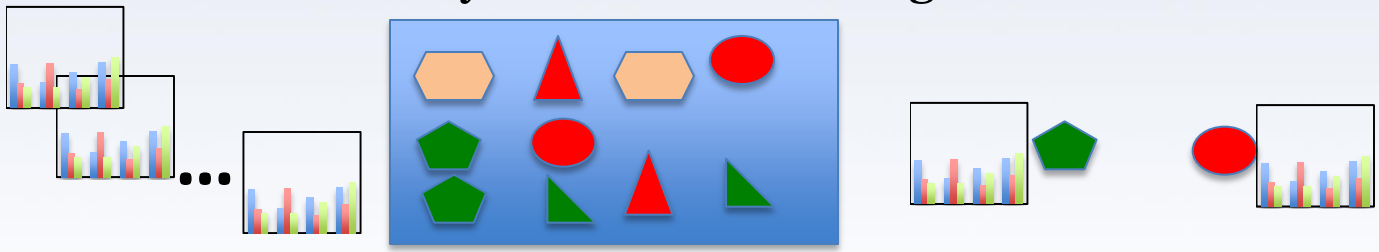
- Entropy analysis
  - Bintropy
    - Shannon entropy
    - Detection method for packing and encrypted binaries
    - Packed and encrypted binaries have greater than 6.67 entropy
  - Metering data have low entropy less than 6.
    - Evaluating the frequency of each byte in fixed block size

Statistical Analysis

- N-gram analysis
  - FilePrint
    - Each file type has its own distinct 1-gram distribution
  - 1-gram distribution of metering data is different from the one of malware
  - Measuring dissimilarity(distance) between two distributions
    - Manhattan distance and Mahalanobis distance

Statistical Analysis

- N-gram analysis
  - Trained Model for malware
    - K-mean clustering & Manhattan distance
    - EX) 10 malware files, K=2 (2 Trained models)
      - Pick 2 random files -> evaluate distributions -> update distribution by K-mean clustering and manhattan distance

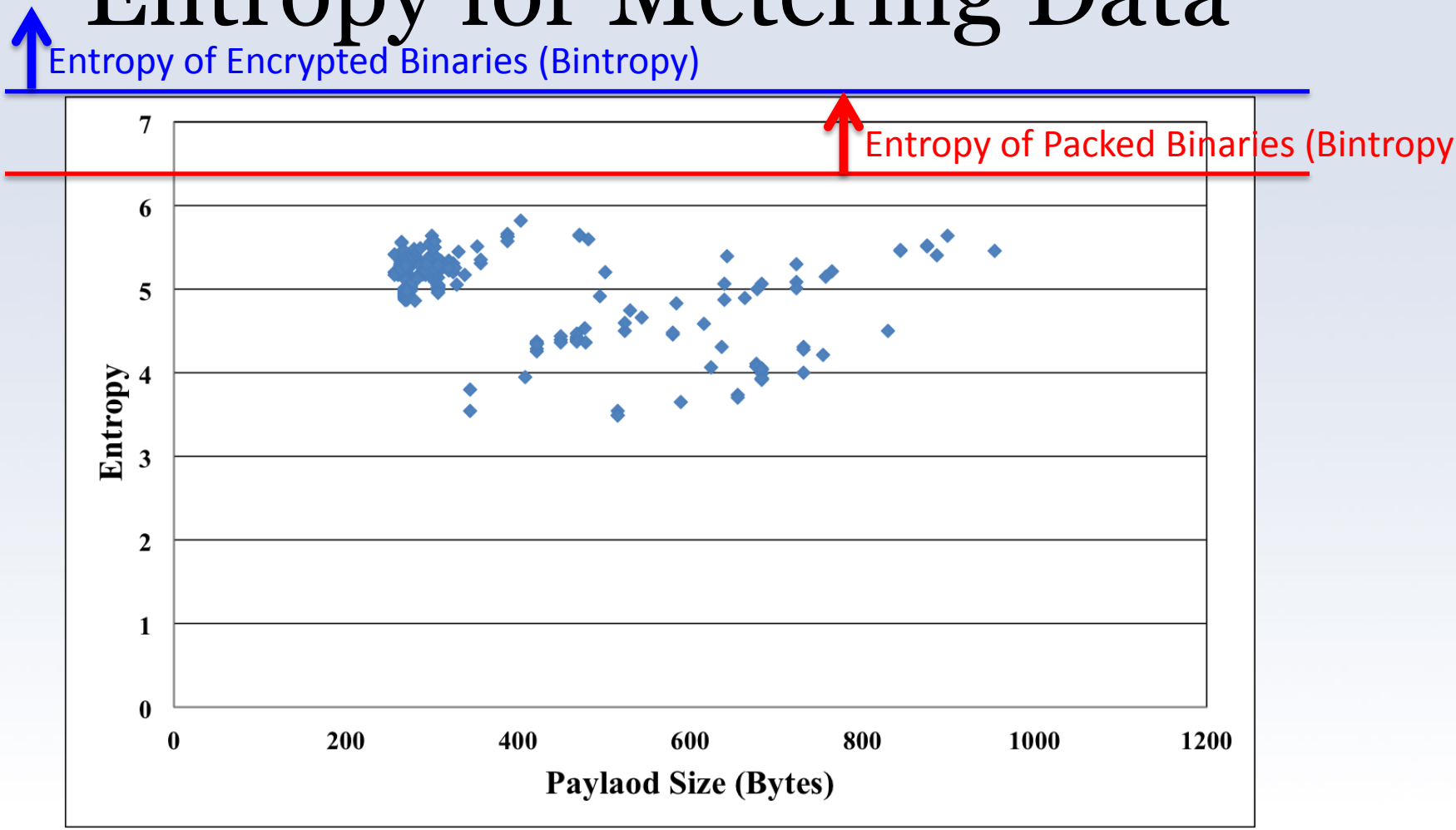


  - Testing Model for metering data
    - Mahalanobis distance to compare to the trained model
    - *Distance(testing file, K-model) > threshold*

Experiments

- Data samples
  - Trained model for 200 malware samples
  - Real 100 metering data files from the TCIPG testbed
- Policy engine implementation
  - Open source GuruX for DLMS/COSEM
  - Intercept API calls of GuruX
- Experiments
  - Entropy & 1-gram distribution & false positive rate & overhead

Entropy for Metering Data



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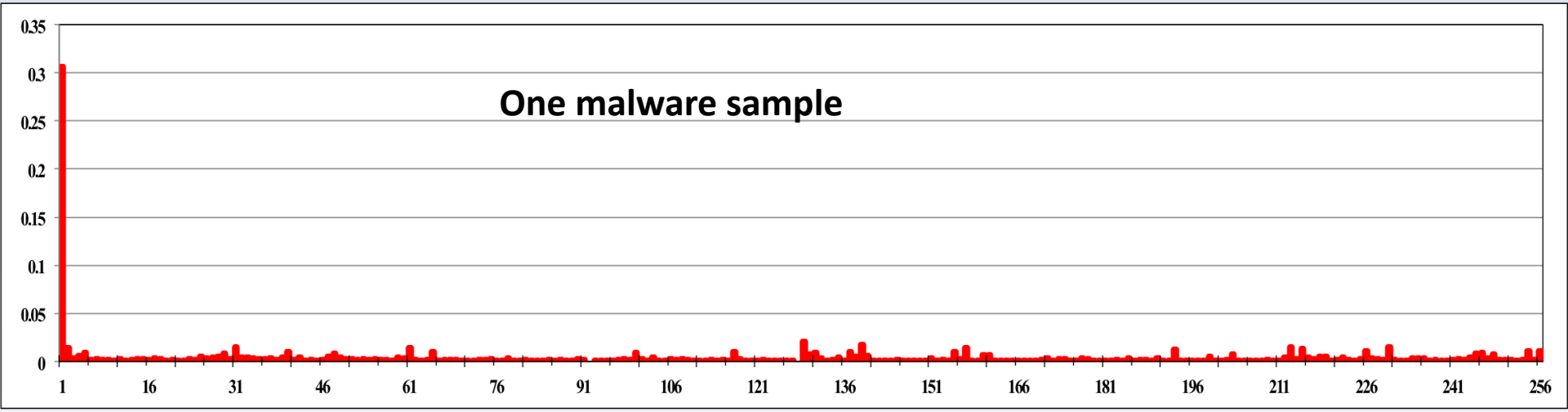
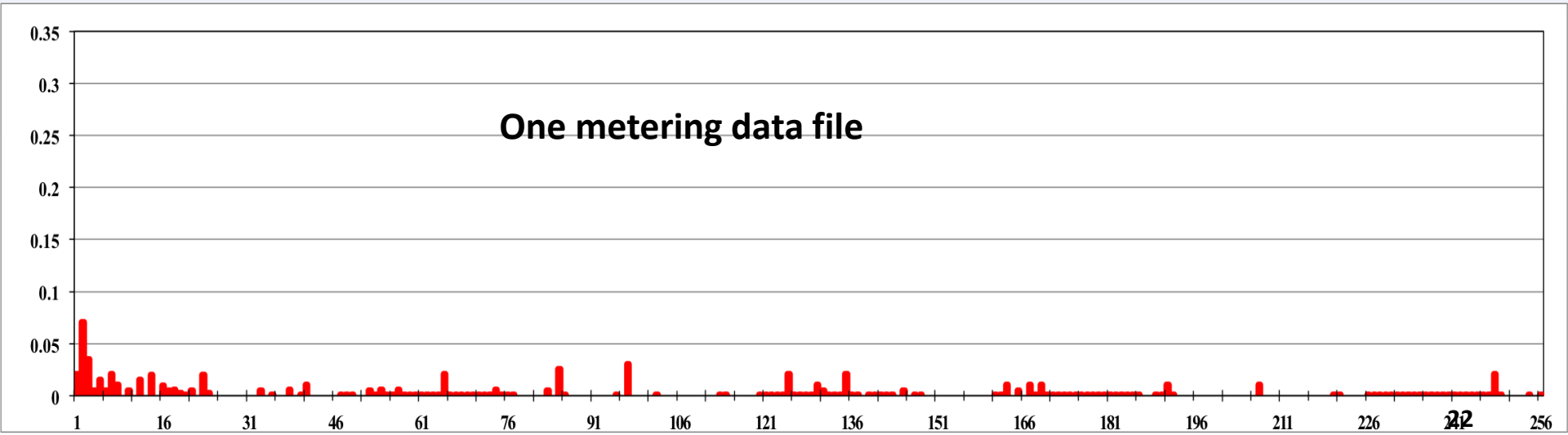
1-gram Distribution





False Positive Rate

- Metering data are recognized as malware
- 0.17% performance overhead

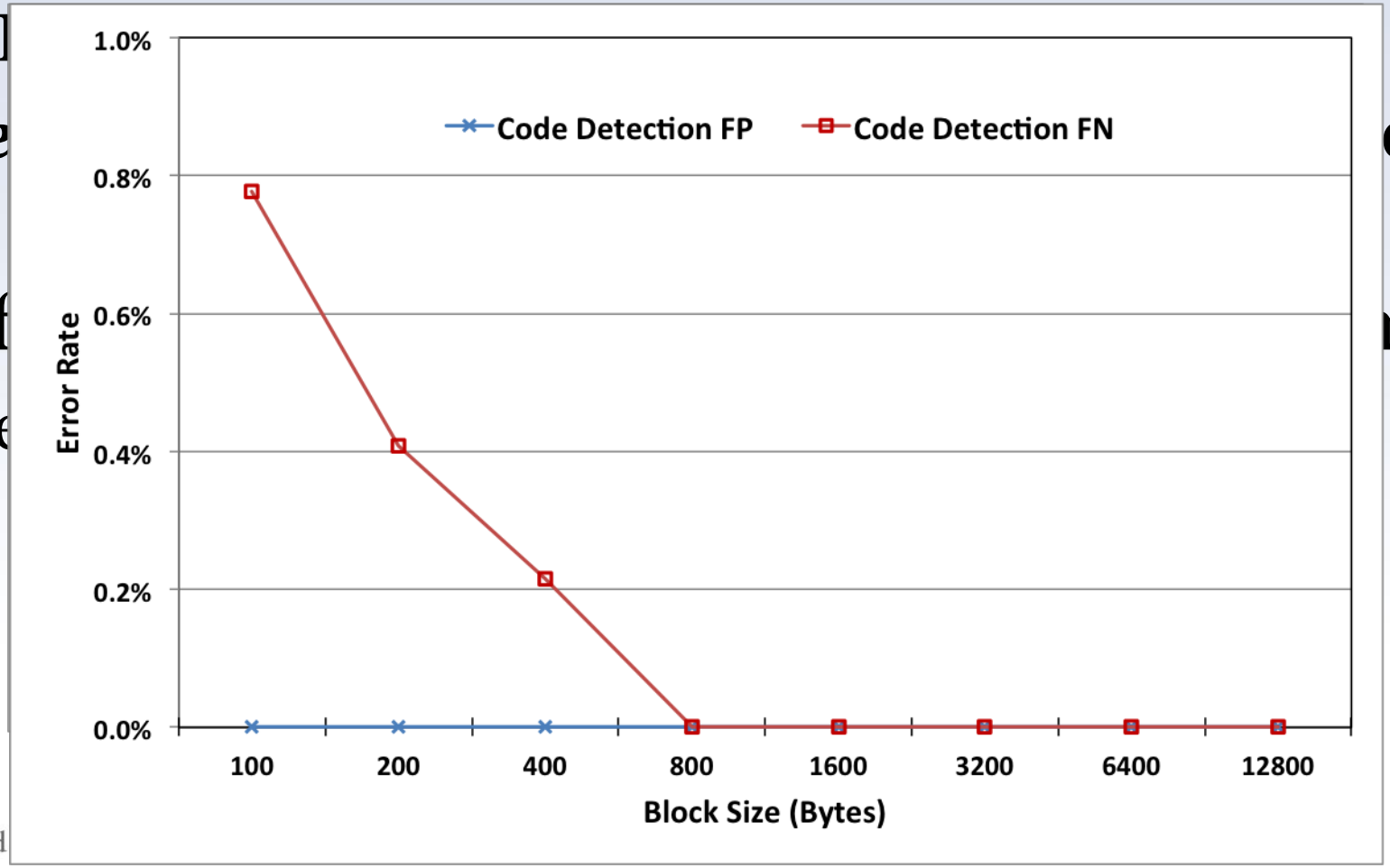
Truncation	50 Bytes	100 Bytes	200 Bytes	500 Bytes	1 KB	2KB
K=1	0%	0%	0%	0%	0%	1%
K=2	0%	0%	0%	0%	1%	1%
K=5	0%	0%	0%	0%	1%	1%
k=10	0%	0%	0%	0%	1%	1%
k=20	0%	0%	0%	1%	1%	2%

Conclusion

- Policy Engine
  - Monitor DMLS/COSEM traffic to detect malware
  - Malware must try to hide as data, but we can ask many policy rules that reveal its presence
  - Use the standard protocol specification and the statistical features of metering data

Current/Future Work

- Improve Accuracy of Malware Detection
  - Al
  - "e 013
- Perf ns
  - Be



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Q & A

Thank You!

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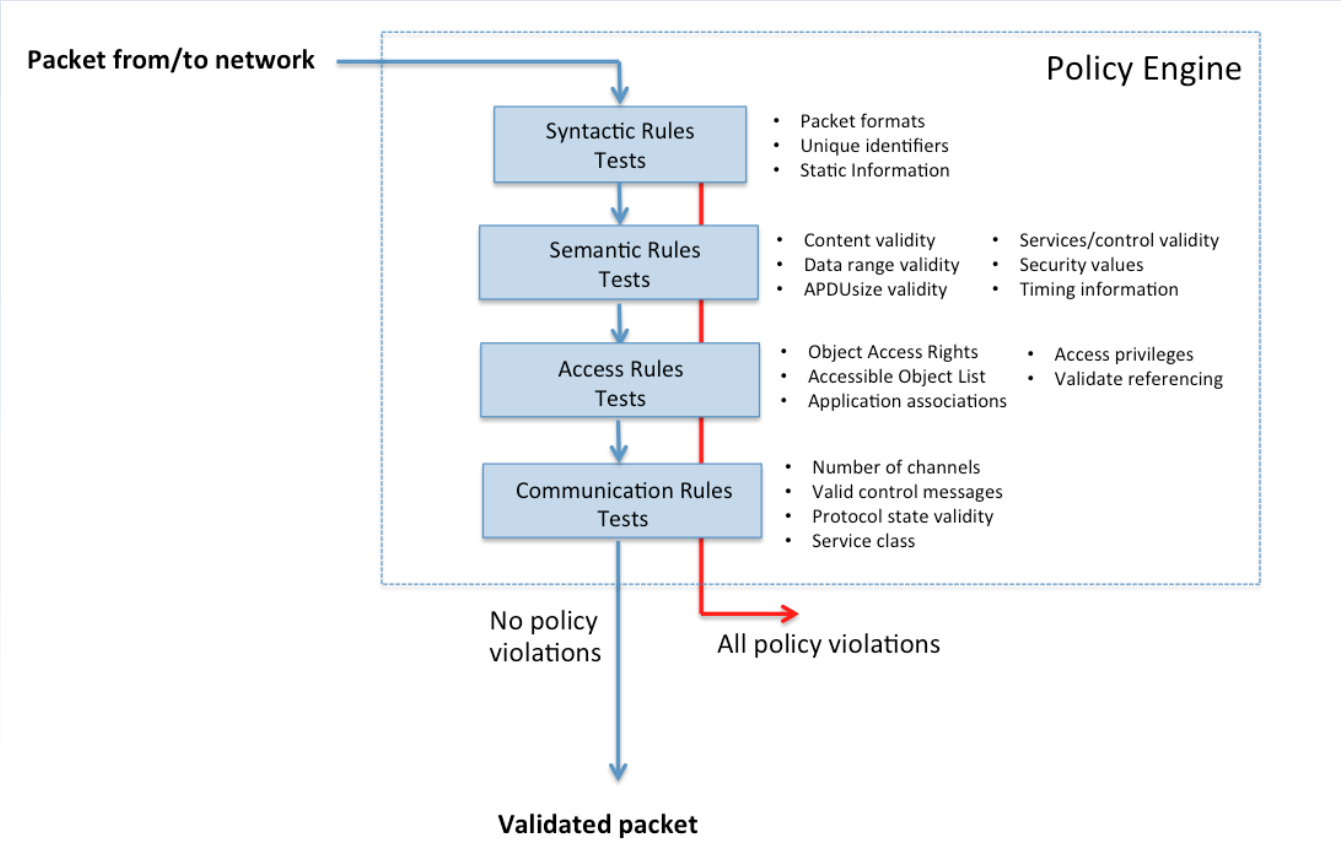
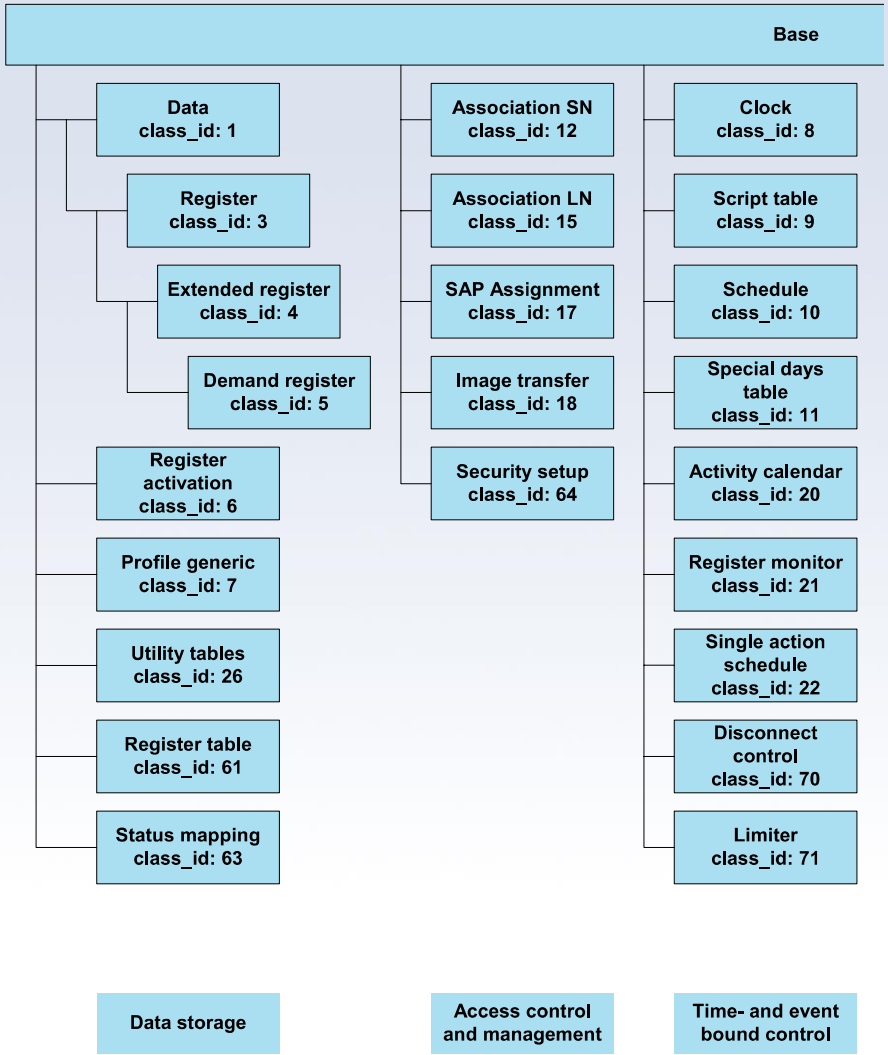
Standard Protocol Analysis



DLMS/COSEM Protocol



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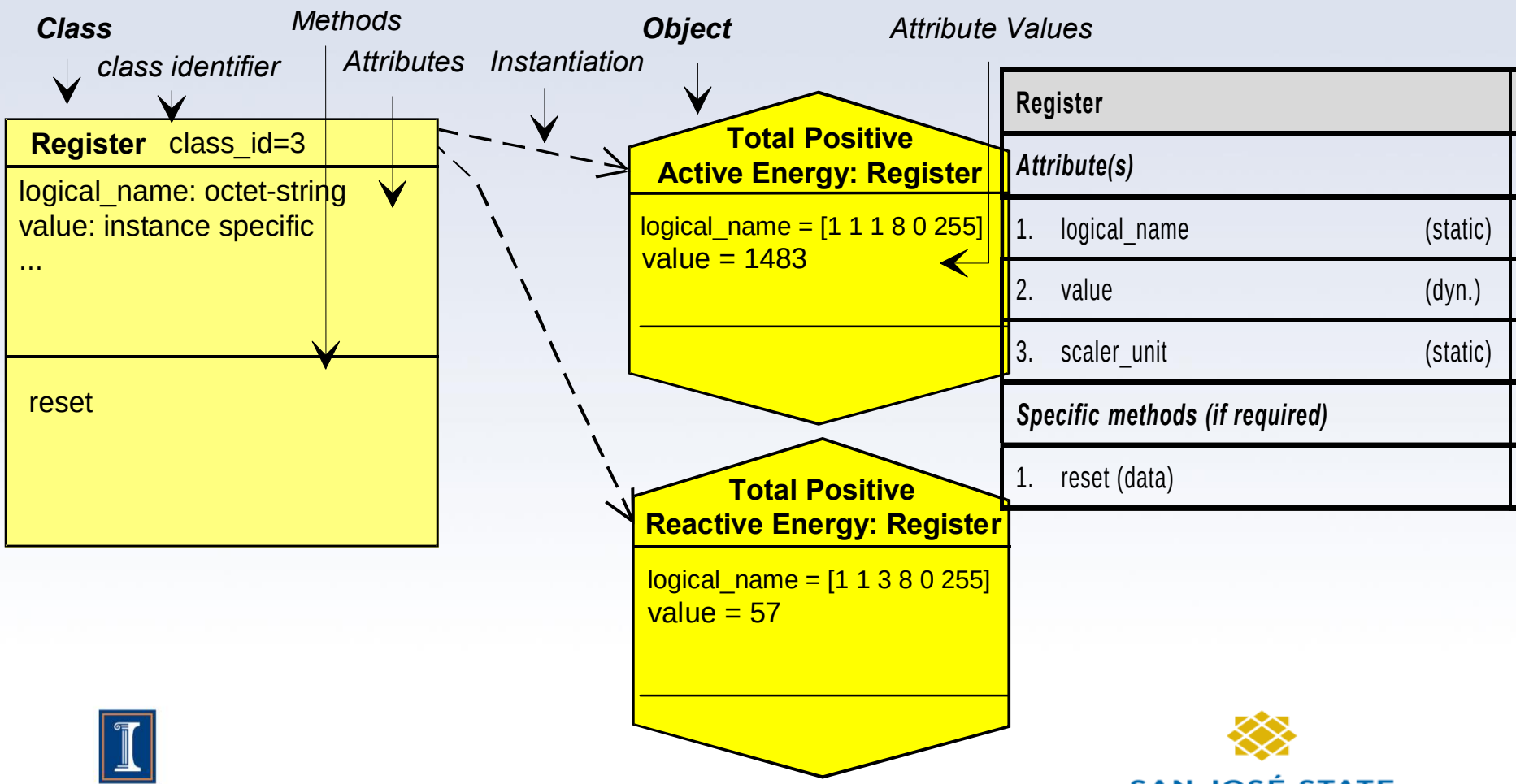
Interface Class



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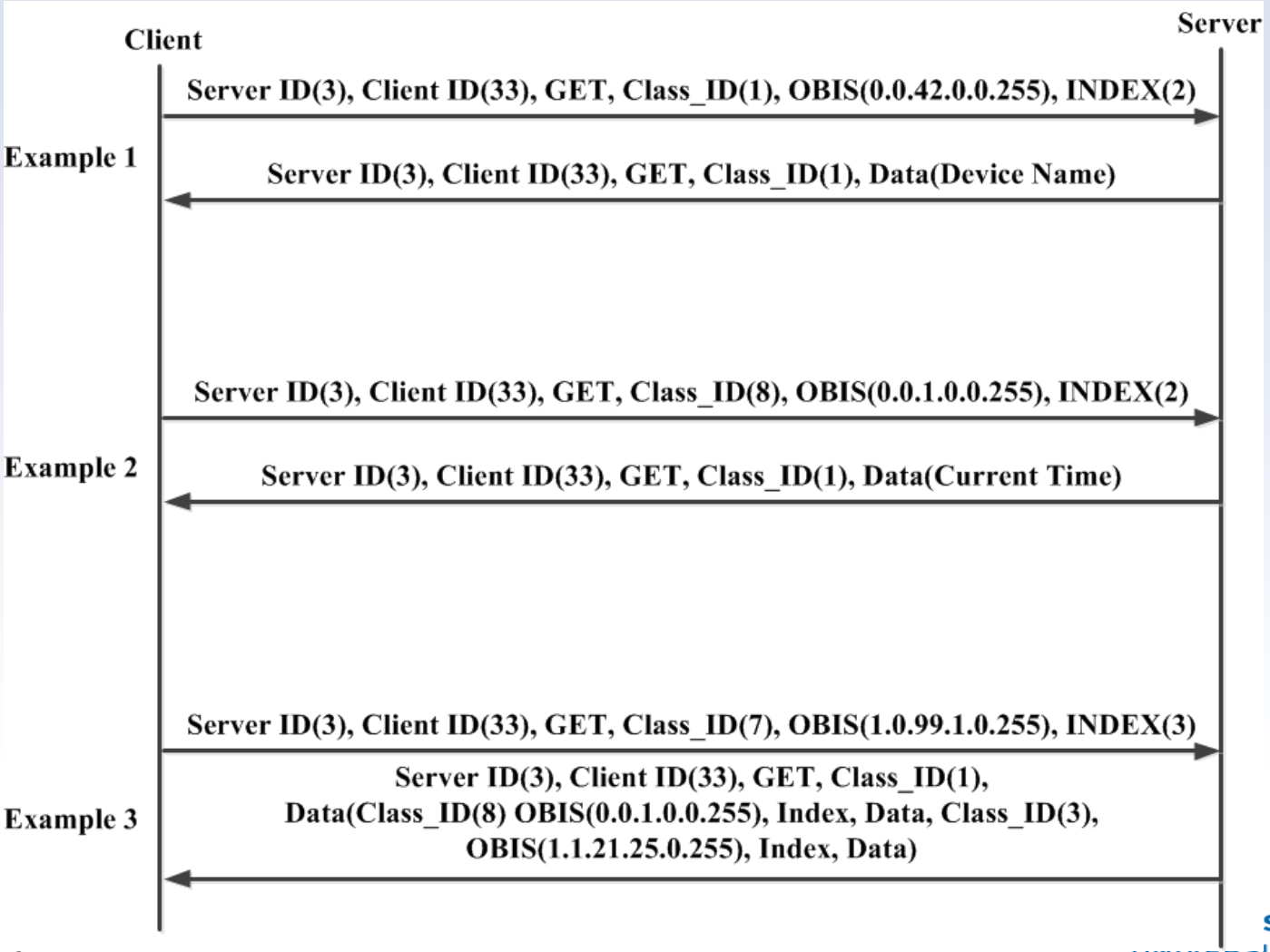
Example of Communication



Result of Bintropy

Table 1. Computed statistical measures based on four training sets.

DATA SETS	AVERAGE ENTROPY	99.99% CONFIDENCE INTERVALS (LOW TO HIGH)	HIGHEST ENTROPY (AVERAGE)	99.99% CONFIDENCE INTERVALS (LOW TO HIGH)
Plain text	4.347	4.066 – 4.629	4.715	4.401 – 5.030
Native executables	5.099	4.941 – 5.258	6.227	6.084 – 6.369
Packed executables	6.801	6.677 – 6.926	7.233	7.199 – 7.267
Encrypted executables	7.175	7.174 – 7.177	7.303	7.295 – 7.312

$$H(x) = -\sum_{i=1}^{n} p(i) \log_2 p(i) \ ,$$

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FilePrint

- 1-gram distributions
  - 256 distinct bytes from 00000000 to 11111111
- Mahalanobis distance

n to represent a class of file types. The resul
eriments indicate that indeed 1-grams perf

- Manhatan distance

$$D(A,B) = \sum_{i=0}^{255} | A_i - B_i |$$

Modeling

- The K-means algorithm that computes multiple centroids is briefly described as follows:
  1) Randomly pick K files from the training data set. These K files (their byte value frequency distribution) are the initial seeds for the first K centroids representing a cluster.
  2) For each remaining file in the training set, compute the Manhattan Distance against the K selected centroids, and assign that file to the closest seed centroid.
  3) Update the centroid byte value distribution with the distribution of the assigned file.
  4) Repeat step 2 and 3 for all remaining files, until the centroids stabilize without any further substantive change.