

Self-organized Collaboration of Distributed IDS Sensors

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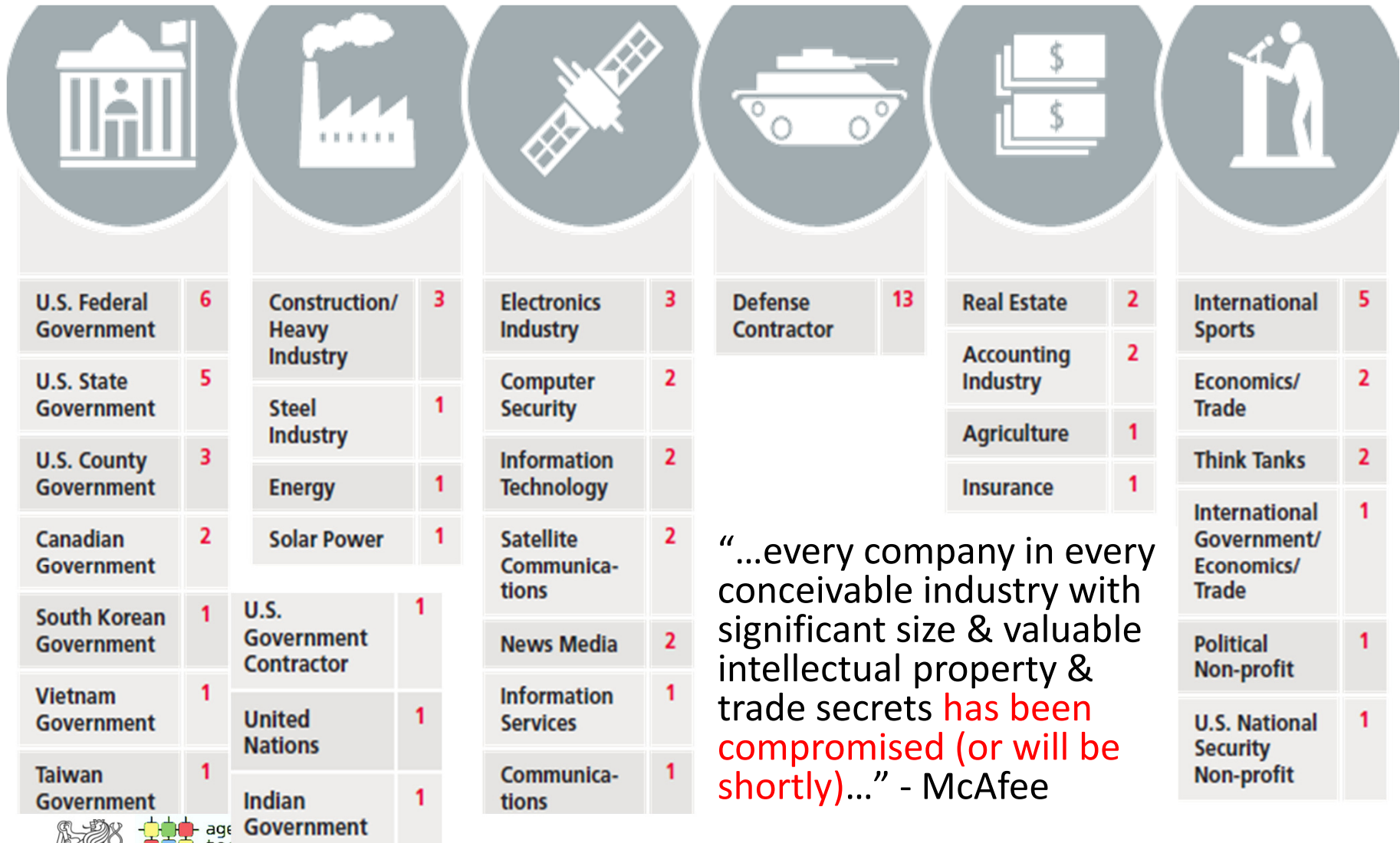
² Cognitive Security, s.r.o., Prague

Network Security – Motivation

- **Advanced Persistent Threats**
 - Strategically motivated
 - Targeted (single/few targets)
- **Threats**
 - Sophisticated industrial espionage
 - Organized crime – credit card fraud, banking attacks, spam
- **Challenges:**
 - High traffic speeds
 - High number of increasingly sophisticated, evasive attacks



All Industry Sectors at Risk

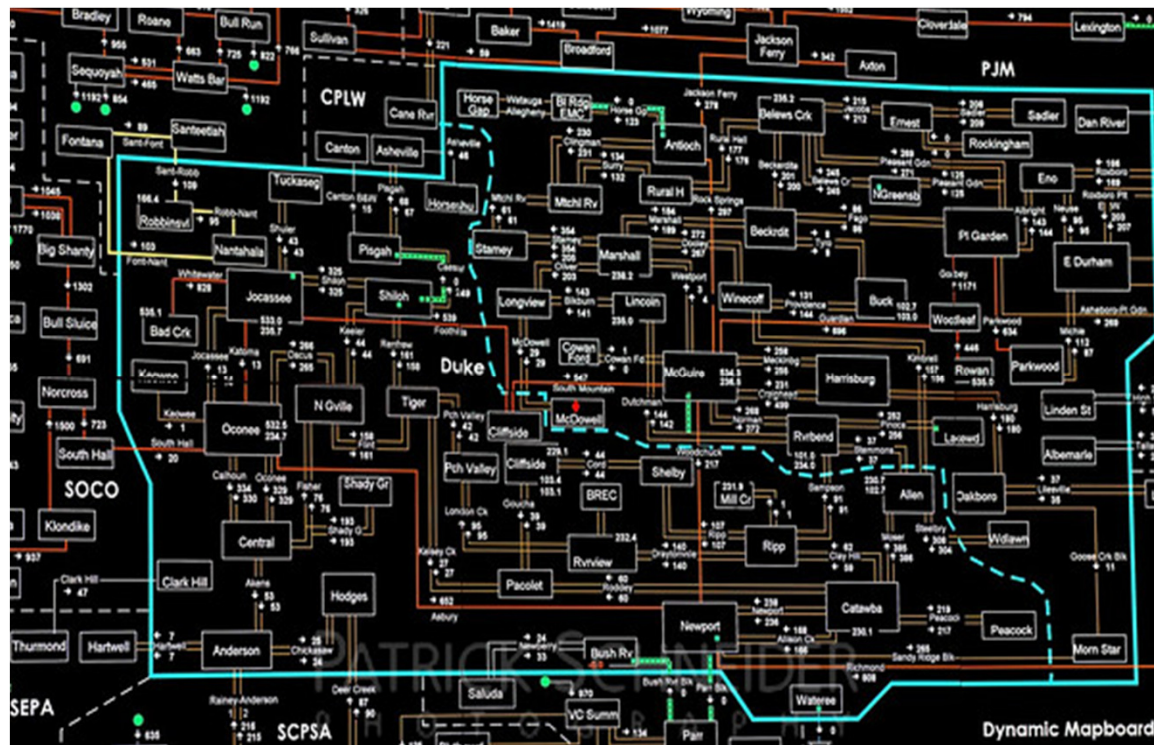


“...every company in every conceivable industry with significant size & valuable intellectual property & trade secrets **has been compromised (or will be shortly)...**” - McAfee



Our Goal

- Use a Collaboration of Multiple Heterogeneous Detectors to create Network Security Awareness



Intrusion Detection



- **Intrusion Detection Systems**

- Deployed on key points of the network infrastructures
- Detects malicious network/host behavior

- **Approaches**

- Host based vs. Network based
- Anomaly detection vs. Signature matching
- Multi-algorithm systems

- **Problem:** Stand-alone IDS is not very effective on

- Cooperative attacks
- Large variability of malicious behavior

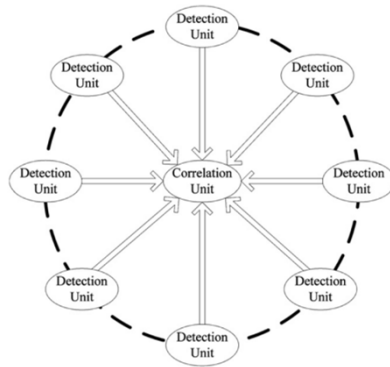
Current Solution? Alert Correlation

- **IDEA: Data fusion of results from more detectors**
- **GOAL: Create global full scale conclusions**
 - Fusion of raw input data or low-level alerts
 - Increase the level of abstraction
 - Reveal more complex attacks scenarios
 - Find prerequisites and consequences

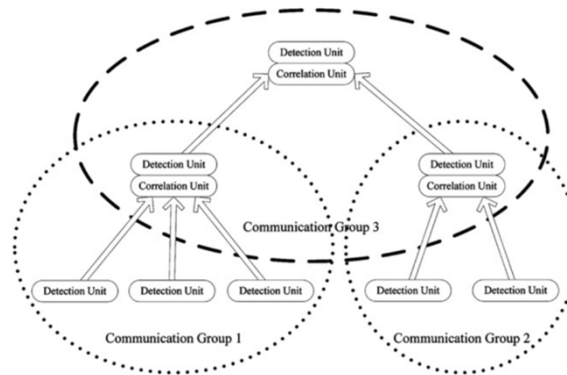
Alert Correlation

- Architectures

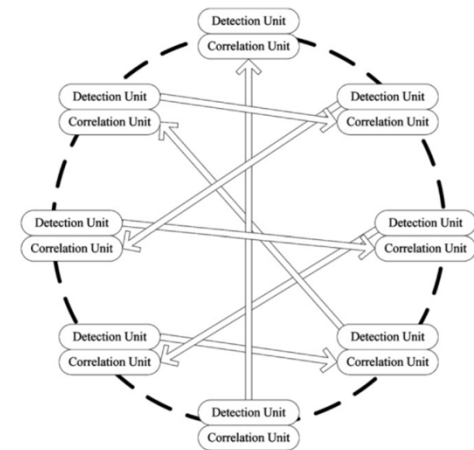
Centralized



Hierarchical

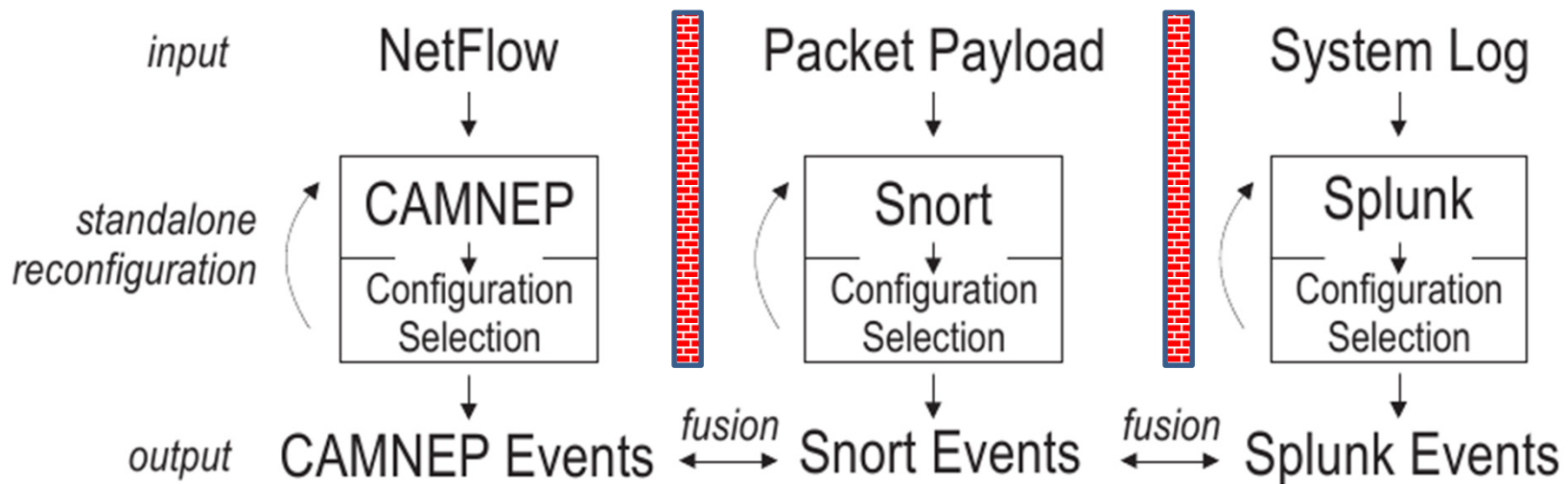


Fully-distributed



Example of Current Architecture

- All detectors work in a **stand-alone** architecture
- More sophisticated detectors can reconfigure based on **local** observations

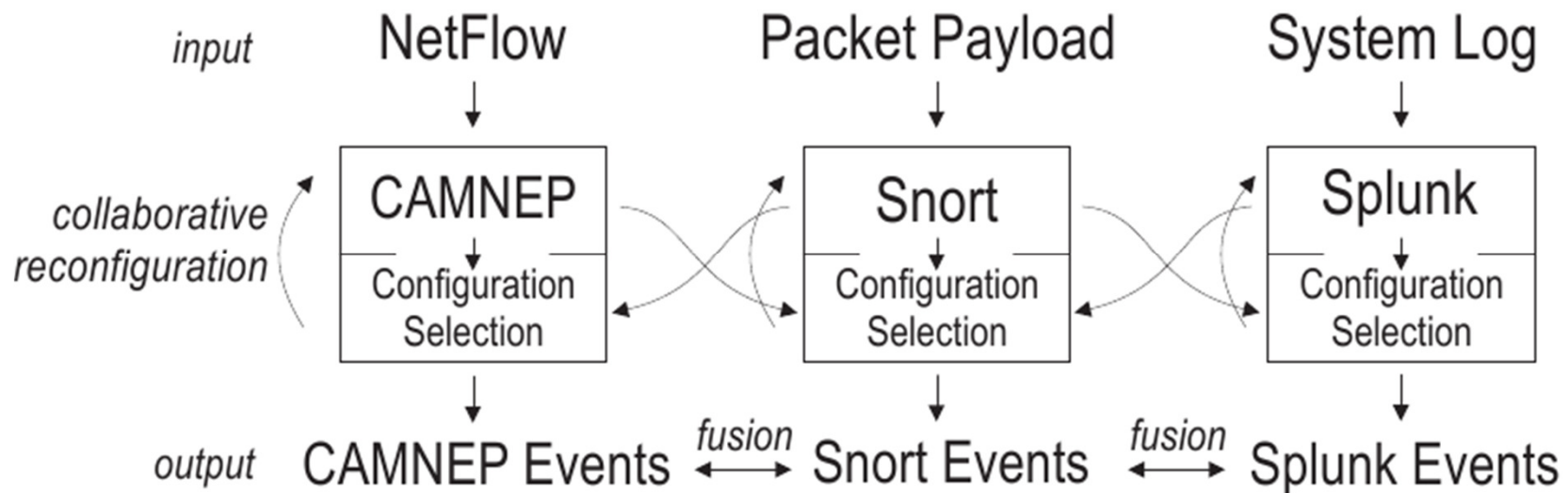


Alert Correlation

- Collects results from more detectors to provide better overall results
- **WEAKNESSES:**
- **It does not provide any feedback to the detectors**
 - Detectors are not aware of the performance of other detectors
 - Detectors require initial (manual) configuration/tuning
- **It does not improve the performance of detectors**

Our Approach

- All detectors work in a **fully distributed** and **collaborative** architecture
- More sophisticated detectors can improve based on observations from other detectors



Assumptions and Requirements

- **Communication**
 - All-to-All, fully distributed
- **Reconfiguration**
 - At least some detectors are able to change their internal states according to the observations
- **Security**
 - Detectors do not provide information about their internal states
- **Strategic Deployment**
 - Detectors are deployed in various parts of the monitored network; network traffic should overlap



Why to communicate and share results?

- **Large variability** of network attacks and threats
 - No single detector is able to detect all intrusions
- **To detect more intrusions, we need more detectors**
 - More detection methods, various locations
- **Many detectors report a lot of same intrusions**
 - They make similar conclusions and mistakes

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Q: Why the detectors generate a lot of FP?

A: Because they: - want to be universal

- want to generate a lot of TP

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Q: Is it a good thing?

- For traditional alert correlation: **YES** (FP reduction)
- For our approach: **NO** (**specialization**)

Specialization

- **IDEA: Detectors communicate in order to be special**
- **Each detector wants:** (specialization allows)
 - to detect unique intrusions → *essential*
 - to minimize the amount of FP → *effective*
- **Each detector does not want:** (specialization prevents)
 - to waste resources on already detected intrusions
- **Specialization in collaboration**
 - Maximizes the overall detection potential of the system

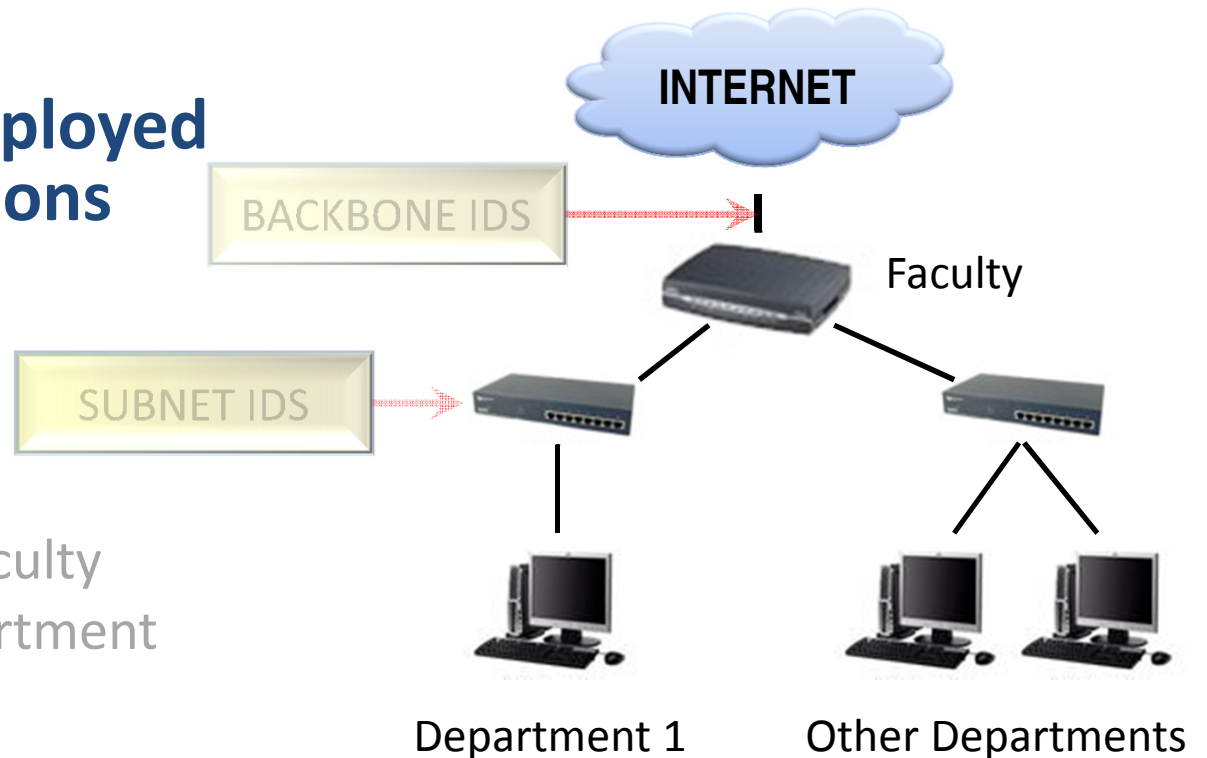
Proposed Collaboration Model

- **Set of feedback functions**
 - Computes the specialization of each detector
 - $f: E_{\text{local}} \times E_{\text{remote}} \rightarrow \mathbf{R}$
- **Set of configuration states**
 - Defines the behavior of each detector
- **Solution Concept / Algorithm / Strategies**
 - Feedback – reconfiguration mapping
 - Suitable for dynamic network environments



Experimental Evaluation - Setup

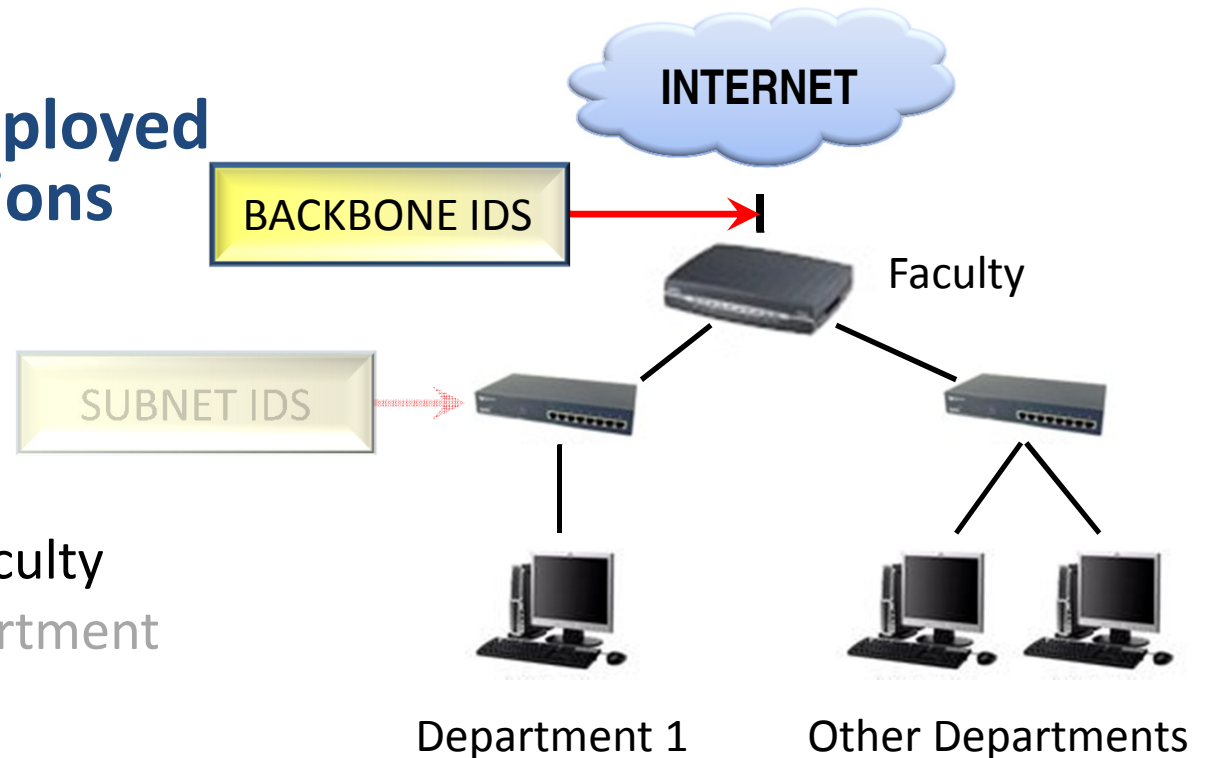
- 2 network IDS deployed in different locations of our University network



- Backbone IDS – Faculty
- Subnet IDS – Department
- 10 hours of network traffic (NetFlow)
- Including samples of malware behavior

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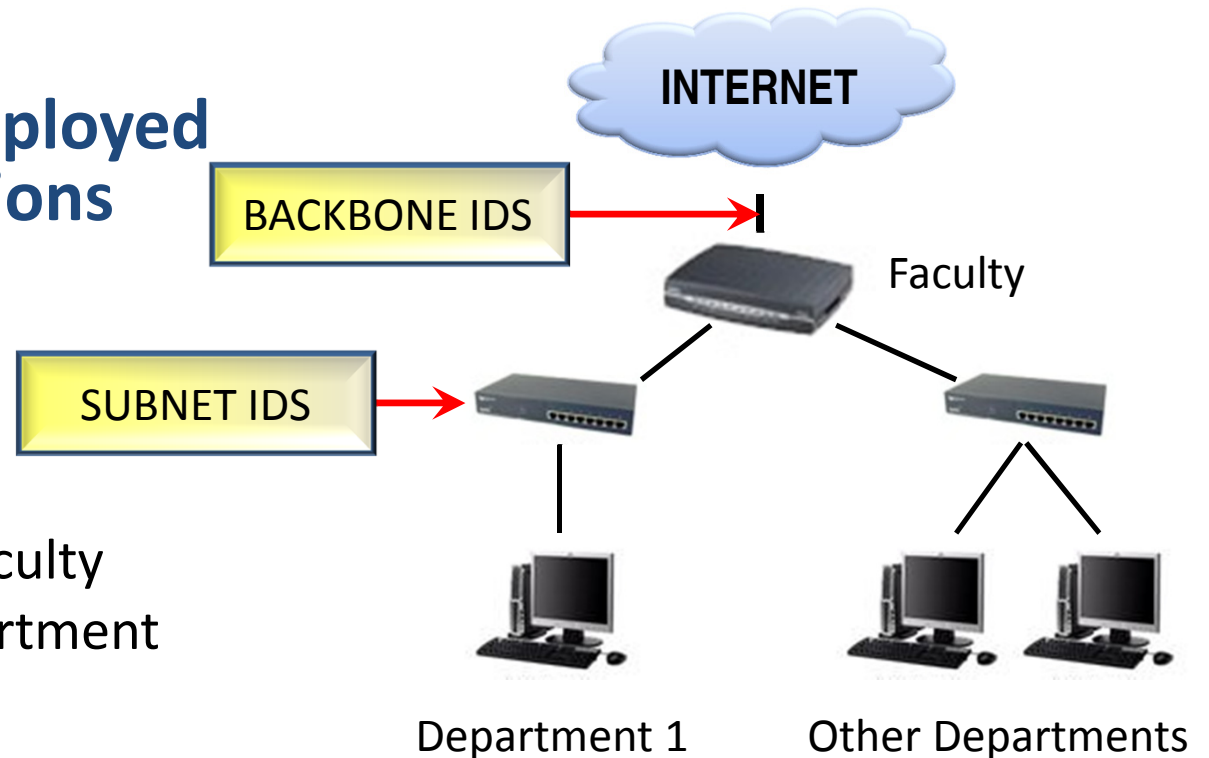
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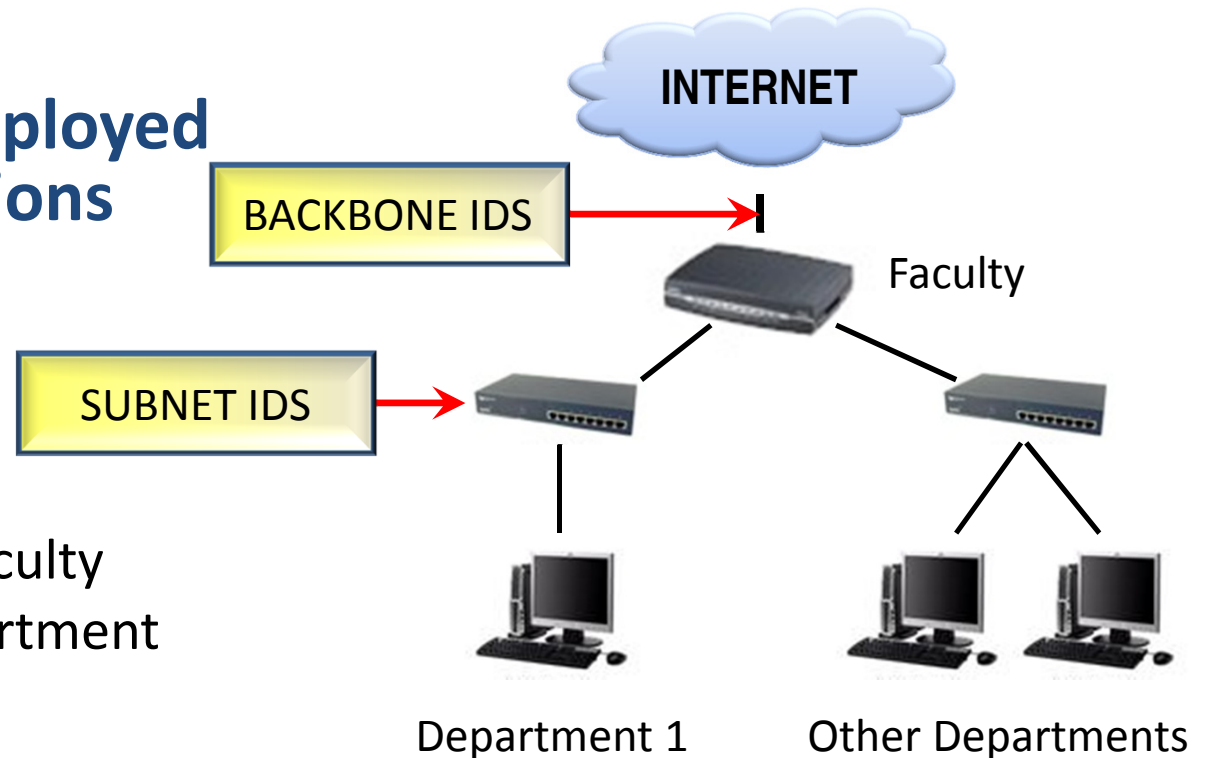
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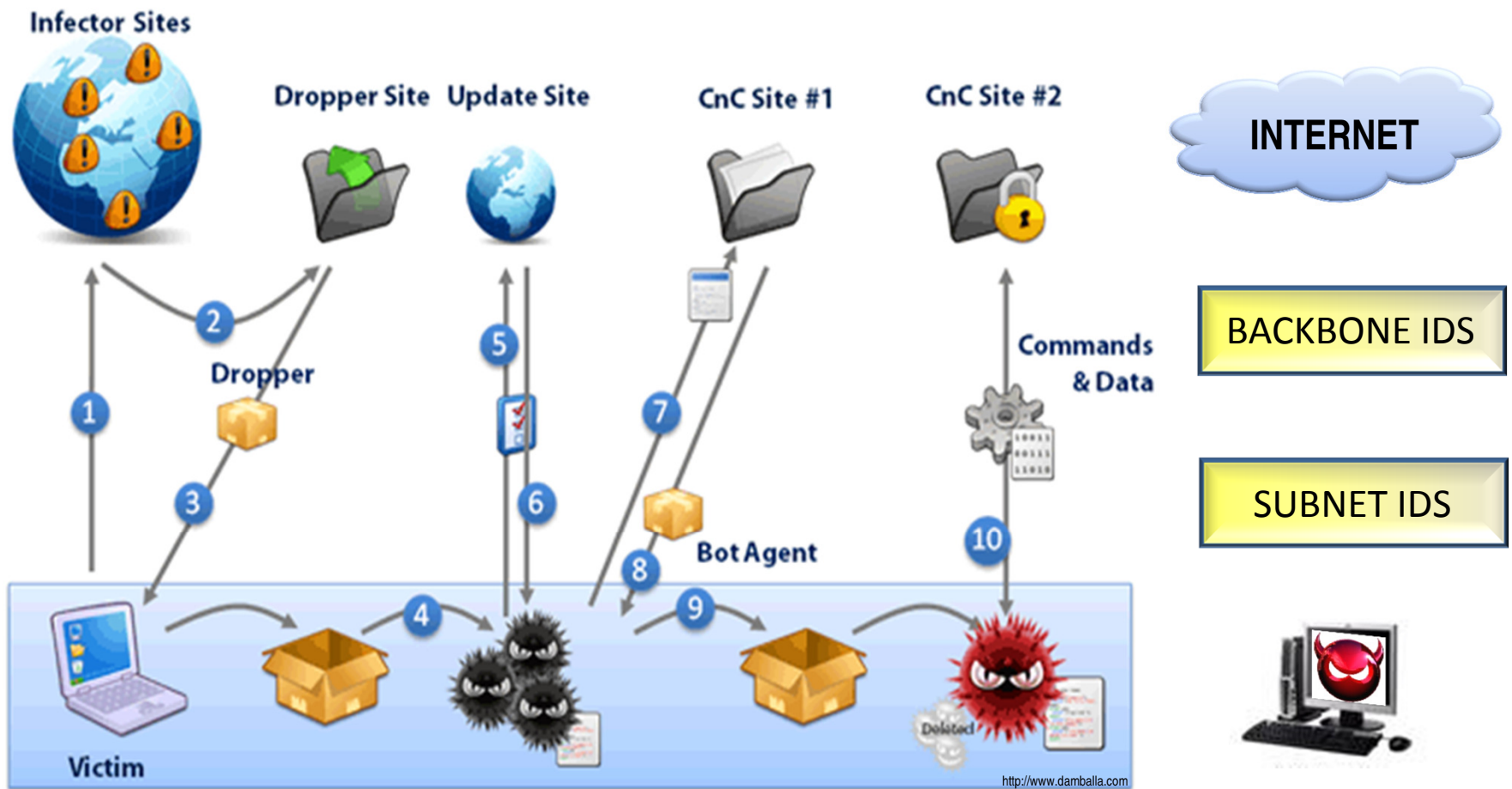
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Experimental Evaluation - Malware

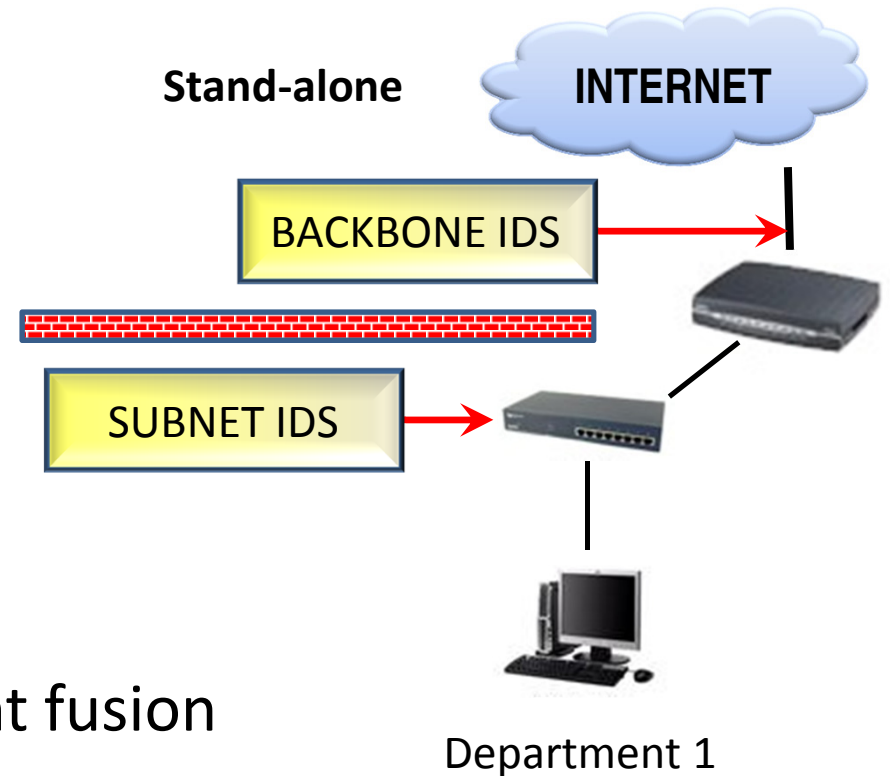


Experimental Evaluation - Model

- **Feedback function is defined as**
 - Uniqueness of generated events
 - Number of alerts that I detected and others did not
- **Set of configuration states**
 - Each detector consists of several detection methods
 - Several opinions have to be aggregated = parameter
 - State = aggregation function within each IDS

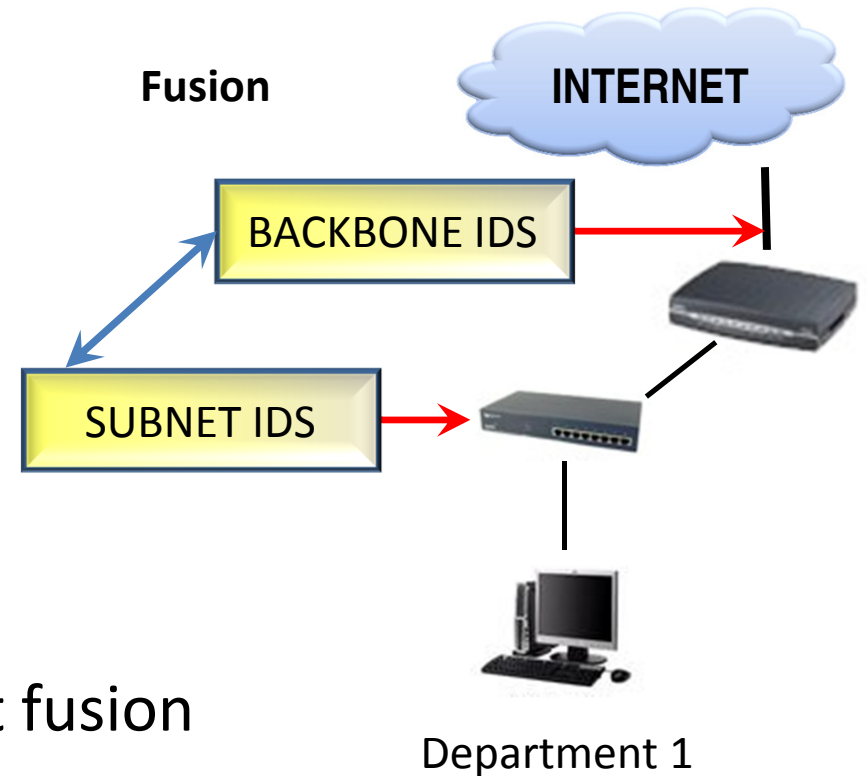
Experimental Evaluation - Strategies

- **Stand-alone**
 - No feedback, No fusion
- **Fusion only**
 - Detectors are connected and exchange their results
- **Fusion + Feedback**
 - Distributed feedback, Event fusion
 - Encourages specialization



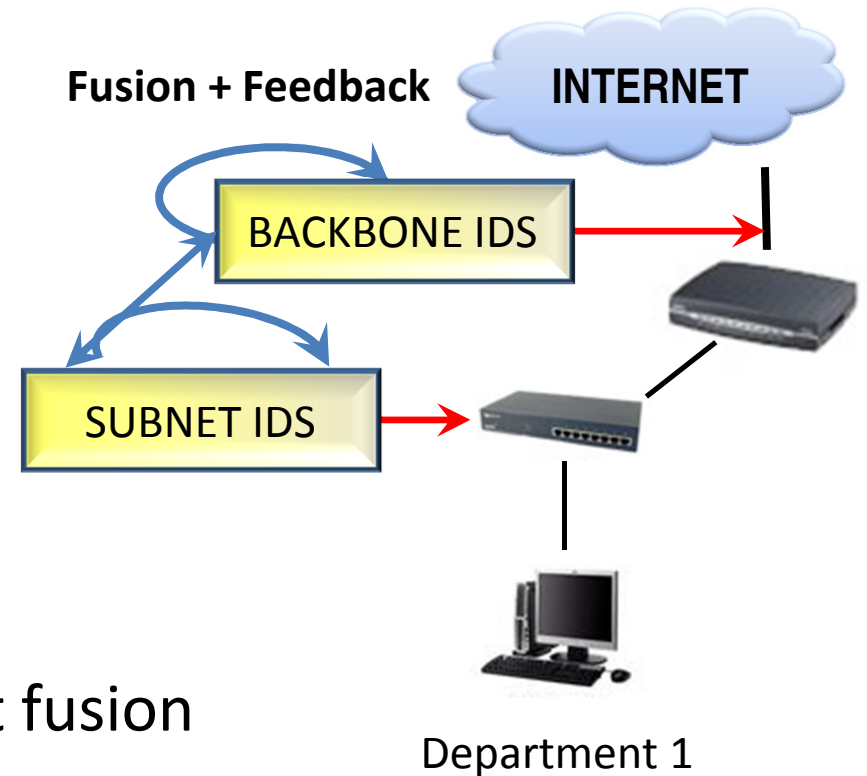
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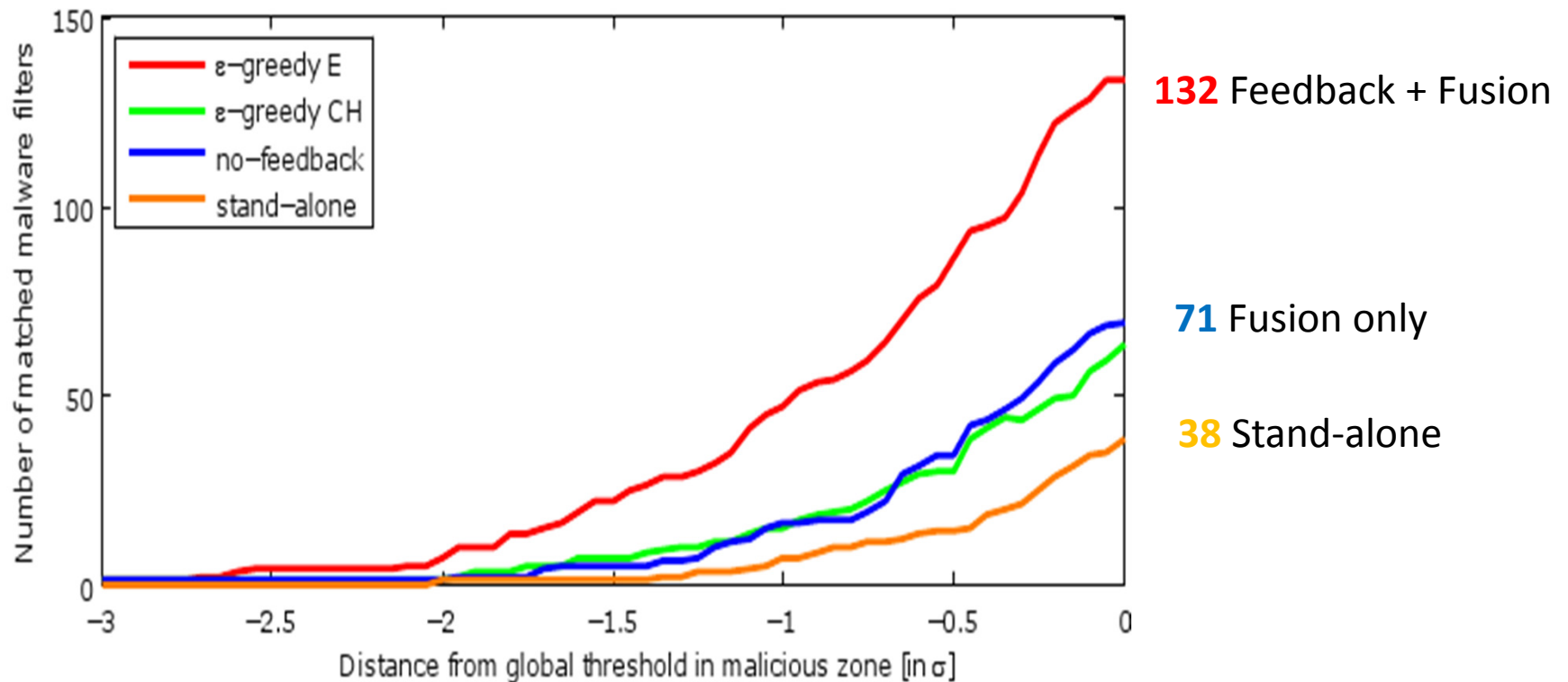


FIRE Epsilon-greedy Adaptation

- **Model consists of configuration states and their uniqueness values (weighted 5 past values)**
- **Algorithm**
 - Detectors exchange events
 - Compute uniqueness of last used configuration
 - Update last 5 uniqueness values for last used configuration
 - With probability p :
 - $p \geq \epsilon$ select most unique configuration
 - $p < \epsilon$ select random configuration

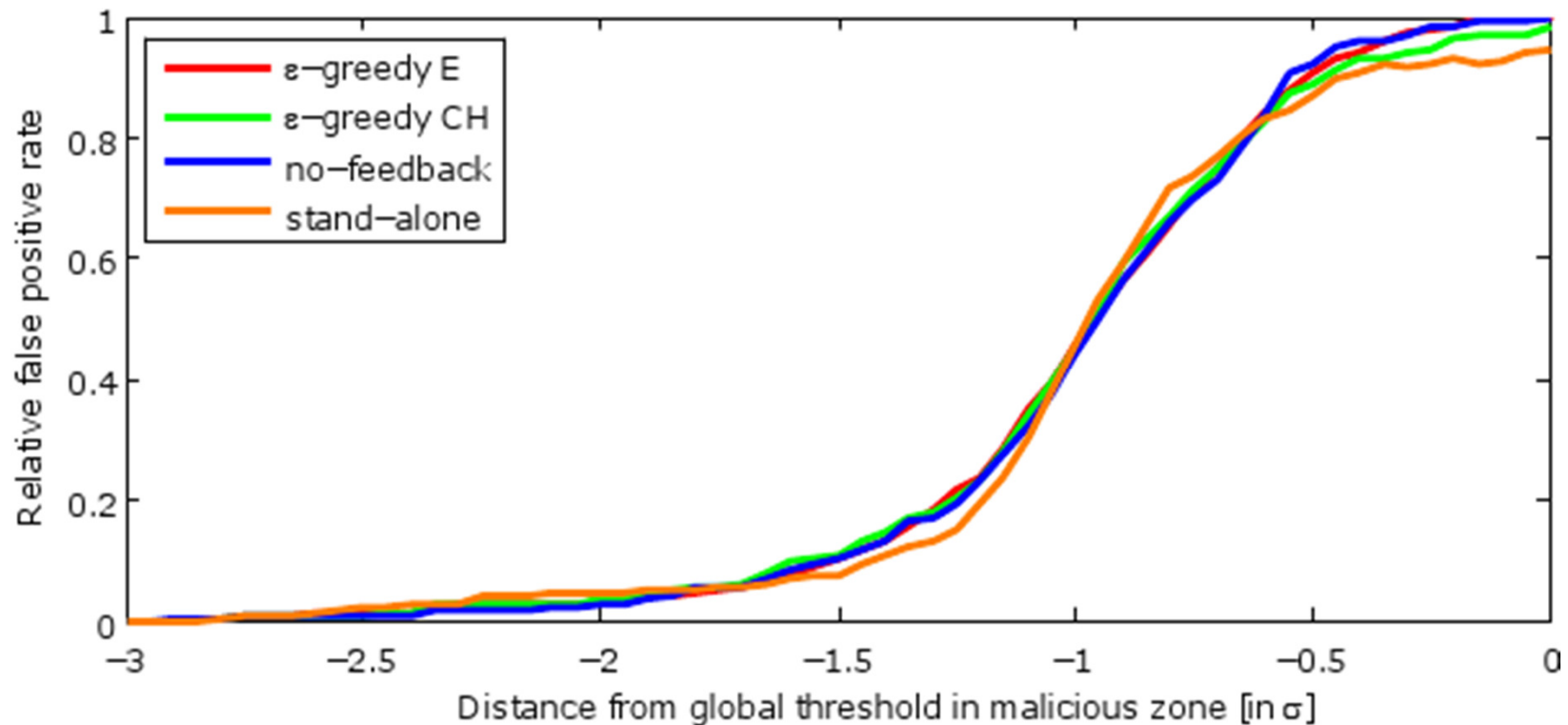
Experimental Evaluation - Results

- Subnet location – # of detected malware samples



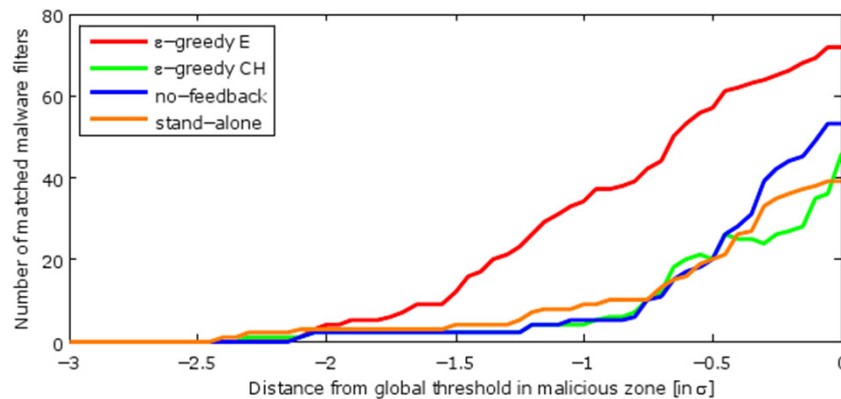
Experimental Evaluation - Results

- Subnet location – relative false positive rate



Experimental Evaluation - Results

- Backbone location – # of detected malware samples

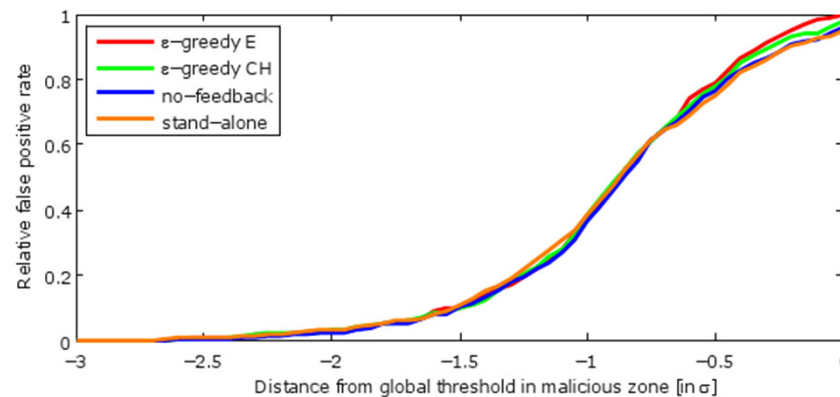


72 Feedback + Fusion

53 Fusion only

39 Stand-alone

- Backbone location – relative false positive rate



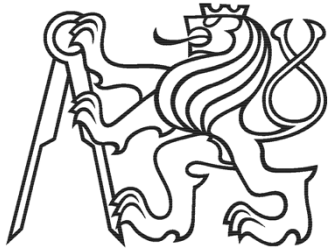
Conclusion

- **Distributed collaboration of heterogeneous detectors**
- **Extends overall detection potential of the system by mutual specialization of the detectors**
- **Future Work:**
 - Other strategy selection techniques
 - More extensive experimental evaluation



Thank You

Questions?

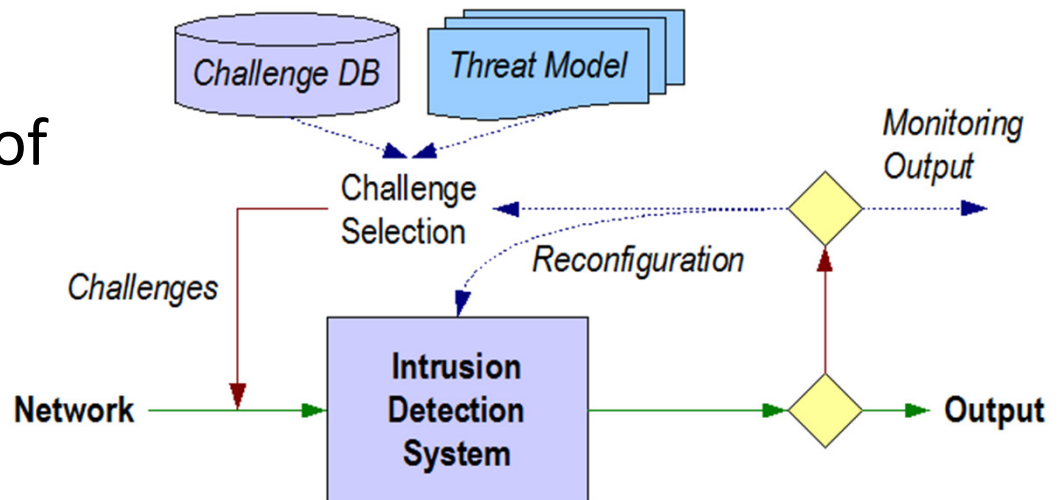


Thank You

Questions?

Local Self-adaptation

- Unlabeled background input data
- Insertion of small set of challenges
 - Legitimate
 - Malicious
- Response evaluation
- Problems: Noise, challenge non-uniformity, distribution, system compromise



Challenge Insertion Control

