# Distributed Anomaly Detection with Network Flow Data

Detecting Network-wide Anomalies

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- 2 Discovering Anomalies in Flows
- Scalable Distributed System
- Exemplary Results



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- 4 Exemplary Results

### 5 Summary

### • Computer networks are crucial to daily life

- banking systems, power plants, your office
- Attacks are more sophisticated and widespread
- How do we protect networks?
- Proactive security is not sufficient (e.g. firewalls)



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Securing Complex Networks	Discovering Anomalies in Flows	Scalable Distributed System	
The Scenario			

- Security cannot be guaranteed
- Detect security and policy violations after their occurence

### Scenario: Small Network

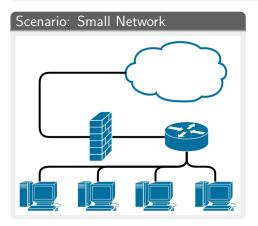
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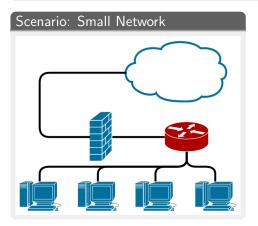


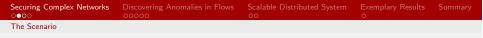
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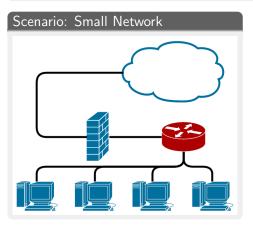


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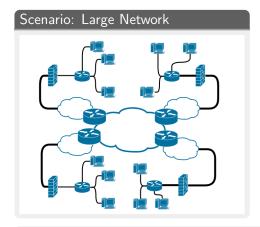
- One common point of ingress
- Complete view of the network
- Flows captured in one place

Securing Complex Networks	Discovering Anomalies in Flows	Scalable Distributed System	Summary
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# Scenario: Large Network

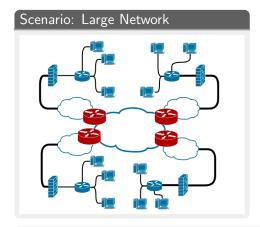
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- Reactive security utilizing distributed IDSs

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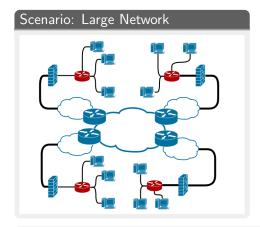
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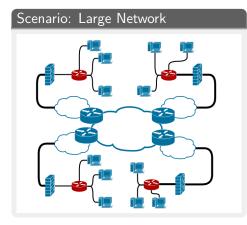
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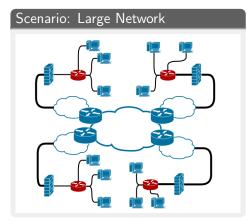
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### Flow Monitoring

- Distributed monitoring with **IsarFlow**
- To collect, aggregate and perform anomaly detection

### **Anomaly Detection**

- To detect unknown problems
  - Attacks or intrusions
  - Irregular operation
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### IsarFlow Architecture

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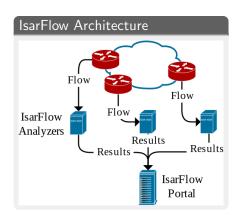
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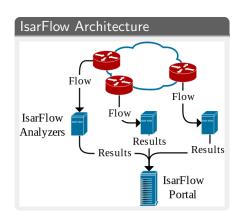


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2 Discovering Anomalies in Flows

### Flow Anomaly

Any network traffic exhibiting unexpected or undesired patterns of communication in flows.

- Malicious Activity
  - (D)DoS
  - Port Scans
  - Worms & Botnets
- Operational Problems
  - Alpha Flows
  - Ingress Shifts (Outages)
  - Large quantities of small packets
- Noteworthy Events
  - Flash Crowds
  - Bittorrent Traffic

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- Highly dimensional data
- Data can be both numerical and categorical (e.g., protocol names)
- Do not contain network payload
- Often contain sampled data
- Vast quantities of information

Intrusion detection is difficult in this problem space

• Feature extraction and summarization is required

- Volume-based feature extraction
- Entropy-based feature extraction



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## Entropy-based Feature Analysis

### Why is Entropy Interesting?

- Every flow feature can be summarized with its entropy
  - $\bullet\,$  e.g., source and destination IP, source and destination port
- Compact representation of all features

### Entropy (H):

- Degree of randomness
- Maximum if all values are equal
- Minimal if probability mass concentrates on one value

### Shannon Entropy (H)

$$X = \{n_i, i = 1, \dots, N\}$$

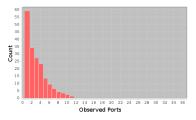
$$H(X) = -\sum_{i=1}^{N} \left(\frac{n_i}{N}\right) \log_2\left(\frac{n_i}{N}\right)$$
$$0 < H(X) < \log_2 N$$

	Discovering Anomalies in Flows		
Entropy		0	

## Entropy-based Feature Analysis

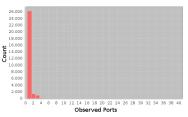
#### Key Property of Entropy

 Entropy measures the concentration or dispersal of a distribution



#### **Normal Traffic**



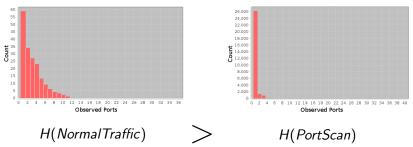


	Discovering Anomalies in Flows	Scalable Distributed System	
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# Entropy-based Feature Analysis

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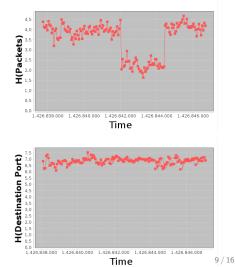
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#### Normal Traffic

**Port Scan Traffic** 

- Select a time window
- Por each window:
  - Build histograms of the desired features
  - Calculate the Entropy of each histogram
  - Build a time series of the entropies
- Choose algorithm to detect unusual patterns
  - K-Means clustering
  - Gaussian Mixture Models (GMMs)
  - Subspace Method

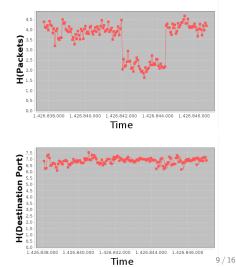


#### Anomaly Detection using Entropy

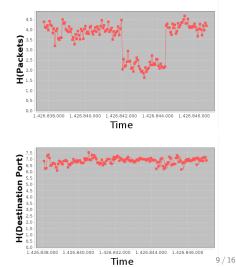
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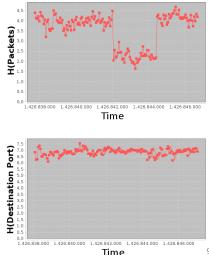
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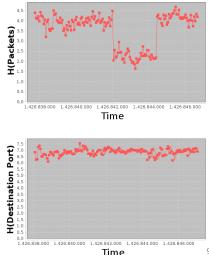
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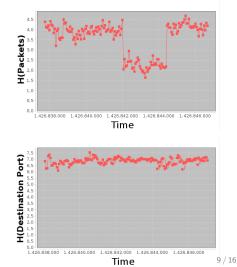
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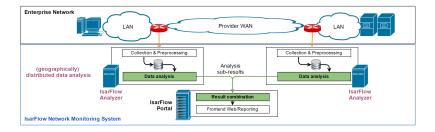
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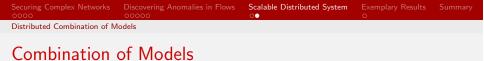


# Distributed Monitoring System

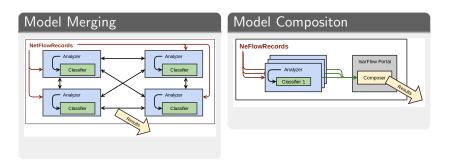
Exemplary architecture: The IsarFlow Network Monitoring System



- Distributed collection, storage and data analysis
  - Scales very well with more analyzers
  - No need to send flow data across WAN
- Detection Algorithms must also scale in a distributed way

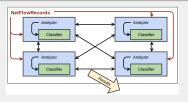


#### How to derive models of normality in a distributed system?



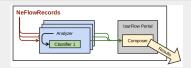
# Combination of Models

#### Model Merging



- Calculate features locally
- Exchange features with other analyzers
- Determine global model of normality - based on all feature information

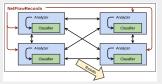
#### Model Composition



- Calculate features locally
- Train classifier with local features
- Classify traffic with local classifier
- Forward local classification result to evaluation instance (Composer)

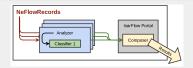
# Combination of Models

#### Model Merging



- + Global Model
- + All analyzer utilize same detection model
- + Learned model can be exchanged
  - Necessity to exchange feature information
  - Features need to be interchangeable

#### Model Composition



- + Local model might be more precise
- + No feature exchange necessary
- + Smaller overhead
  - Model might not be interchanged
  - Composer has to be trained

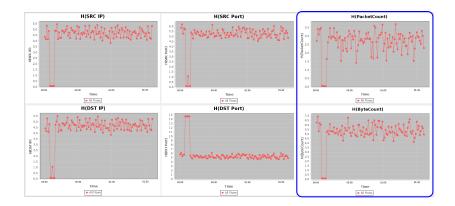
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Capabilities of Entropy

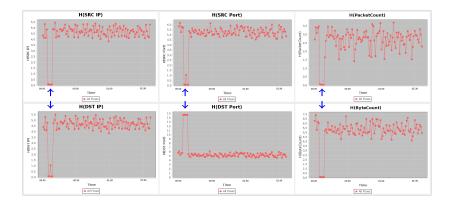
# Example: PortScan Entropy Fingerprint



Securing Complex Networks Discovering Anomalies in Flows Scalable Distributed System Exemplary Results

Capabilities of Entropy

## Example: PortScan Entropy Fingerprint



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# Summary and Outlook

#### Summary

- Reactive traffic monitoring is crucial
- Challenges in large enterprise networks
  - Large amount of unsampled flow data
  - Needs distributed collection and data processing
- Entropy as promising feature
  - Difficult to cope with distributed data
  - Approach requires efficient data combination

### Outlook

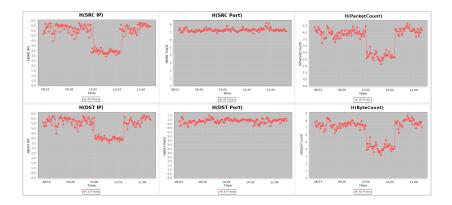
- Thorough study of flow data from a large enterprise network
- Evaluation of feature extraction and classifiers
- Study of detection precision and accuracy

	Discovering Anomalies in Flows	Scalable Distributed System	Summary
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### Thank you

#### THANK YOU FOR YOUR ATTENTION

### Example: DDoS Reflector Attack detection

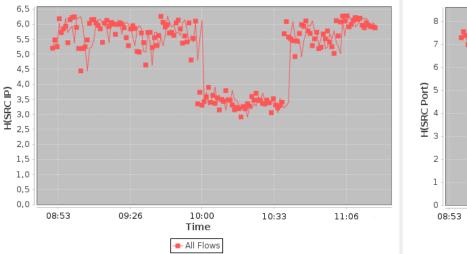


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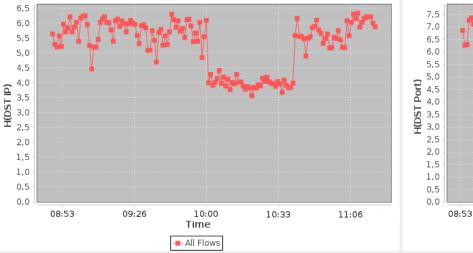
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# Example: DDoS Reflector Attack detection

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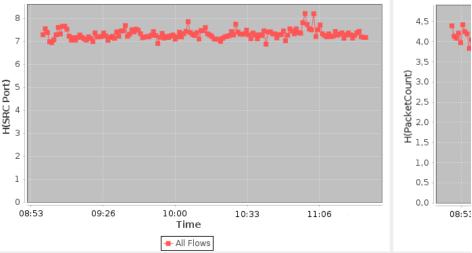


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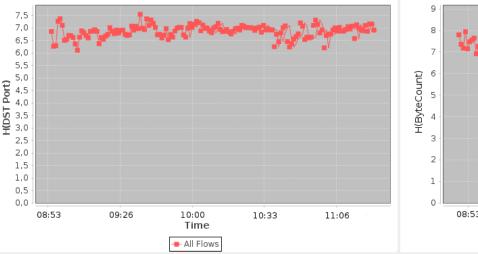
### H(SRC Port)



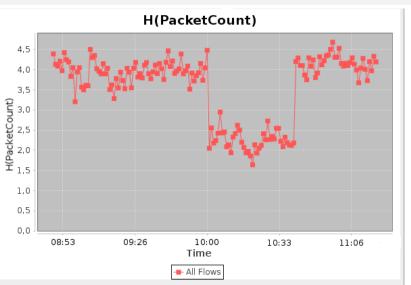
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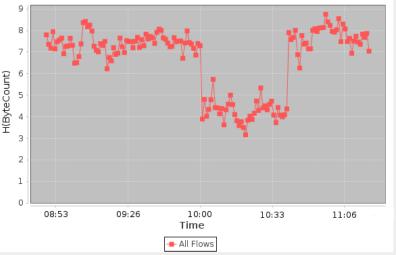


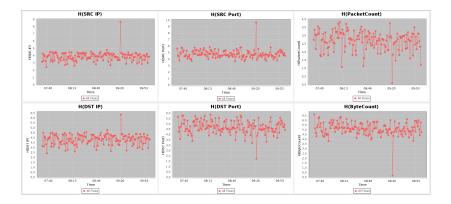
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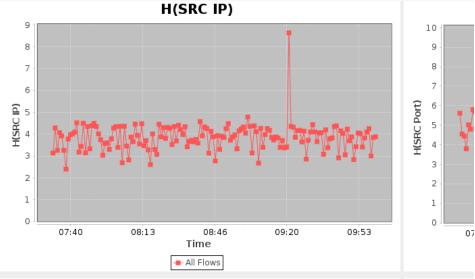


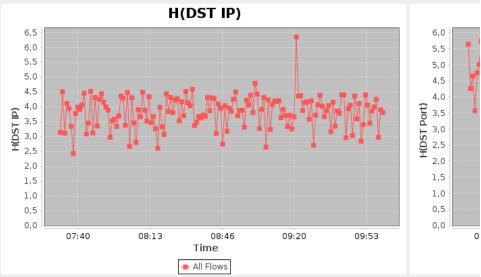
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#### H(ByteCount)



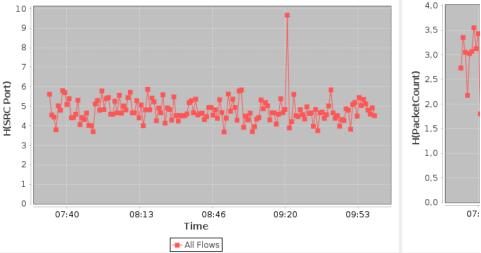




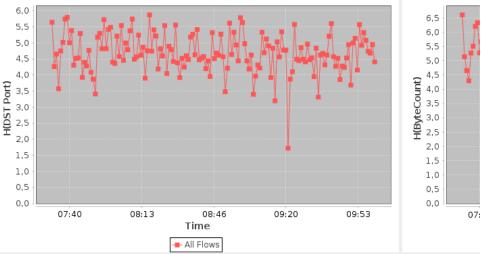


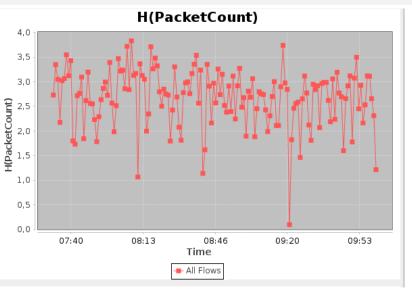


### H(SRC Port)



### H(DST Port)





### H(ByteCount)

