CAMNEP: Multistage Collective Network Behavior Analysis System with Hardware Accelerated NetFlow Probes

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Supported by Czech Ministry of Education grants 6383917201 (CESNET), 1M0567, 6840770038 (CTU) and

CERDEC/ITC-A projects N62558-07-C-0001, W911NF-08-1-0250

Overview



- Network Intrusion Detection Systems
- Anomaly Detection Models
- Trust-Based Anomaly Integration
- Experimental Results

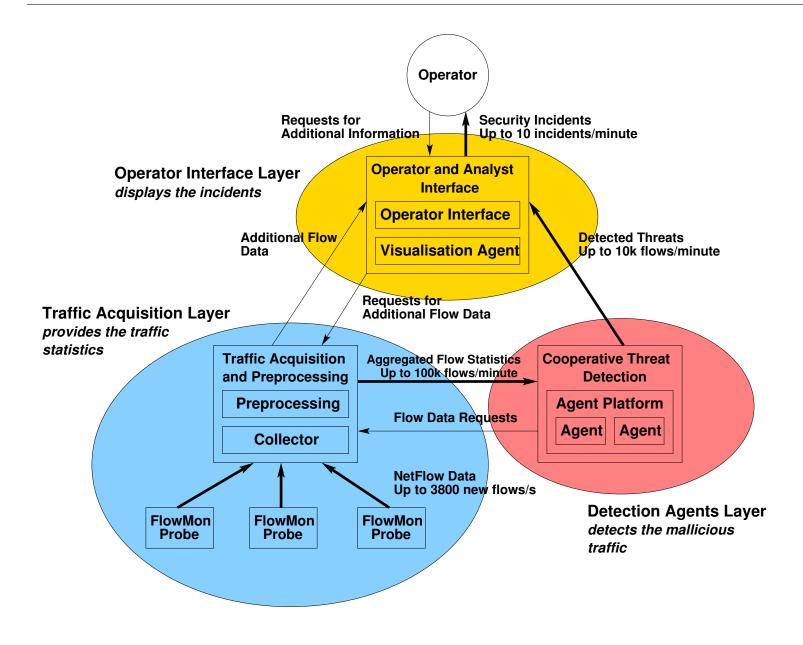
Network Intrusion Detection



- Identification of attacks against hosts or networks from the network traffic observation
 - Signature based detects patterns in packet content
 - Stateful protocol analysis anomalies in TCP protocol state sequences
 - Network Behavior Analysis (NBA) identifies attacks from traffic statistics
- Current Challenges
 - False positives legitimate traffic labeled as malicious
 - False negatives malicious traffic classified as legitimate
 - Performance high network speed, near-real-time results
- Our Contribution: Efficient algorithm for integration of NBA methods
 - Linear with traffic
 - Improves the classification rate by multi-layer combination
 - Based on extended trust modeling

System Architecture

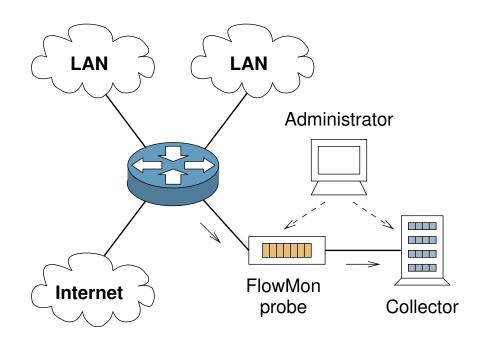




High-Speed Network Traffic Acquisition



- Probes observe the traffic at the wire speed
- Each probe generates NetFlow traffic statistics
- Results are stored and preprocessed in collector servers
- Hardware acceleration necessary for high-speed networks



Hardware Accelerated FlowMon Probe



Requirements:

- traffic characteristics change heavily in time network probes must behave reliably in all possible cases
- capable of generating NetFlow traffic statistics
- work at wire speed (1Gbits/sec 10Gbits/sec)

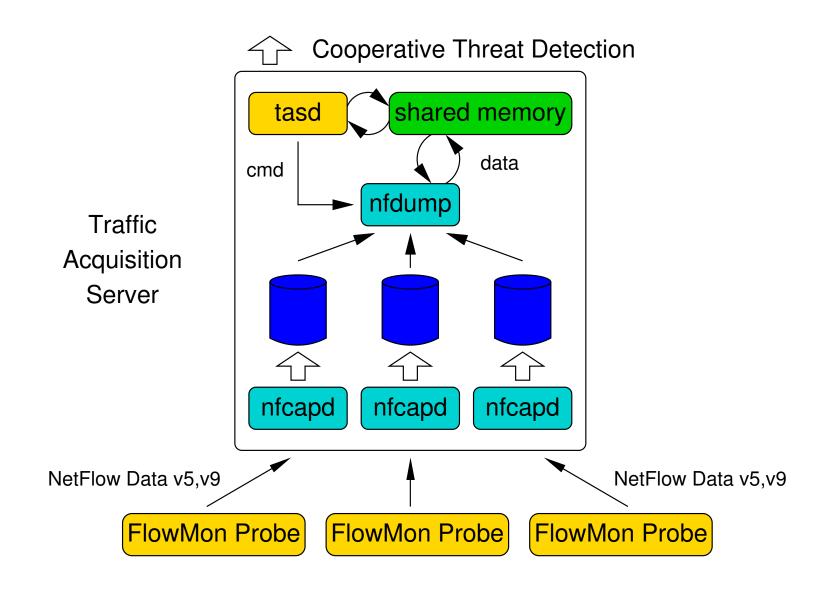
FlowMon Probe:

- developed in Liberouter project
- hardware accelerated network card based on COMBO hardware
- high performance and accuracy
- handles 1Gbits/sec and 10Gbits/sec traffic at line rate
- exports acquired NetFlow data to different collectors



Traffic Acquisition Server Architecture

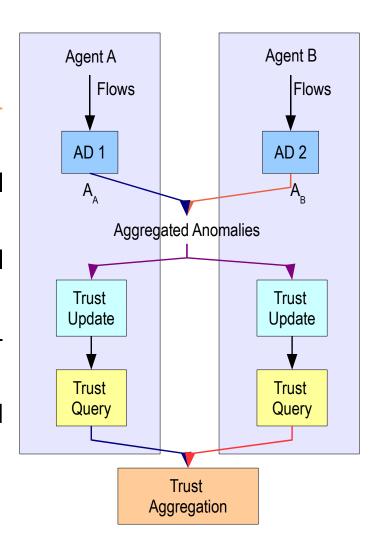




Detection Process Overview



- Each agent based on one anomaly detection method
- Input: NetFlow statistics, same for all agents
- Anomaly: aggregated from individual agent's anomalies
- Update: heterogenous trust model are updated, each has a different structure
- Query: all agents evaluate all flows, and aggregate the output



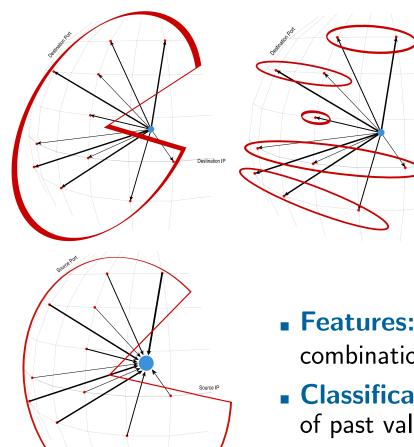
Anomaly Detection Input (simplified)



Duration	Proto	Src IP Addr:Port	Dst IP Addr:Port	Flags	Pack.	Bytes
0.000	TCP	192.168.195.164:1086	192.168.10.12:445	.A	2	84
0.000	TCP	62.97.162.208:3417	192.168.192.83:1172	.AP	1	42
0.577	TCP	192.168.195.132:2544	194.228.32.3:80	.A.R	3	126
0.576	TCP	192.168.195.132:2545	194.228.32.3:80	.A.R	3	126
0.000	UDP	192.168.60.31:4021	192.168.19.247:53		1	55
0.000	UDP	192.168.19.247:53	192.168.60.31:4021		1	149
0.000	UDP	192.168.60.31:4021	192.168.60.1:53		1	55
0.000	UDP	192.168.60.31:4020	192.43.244.18:123		1	72
30.276	TCP	192.168.192.170:61158	71.33.170.53:1358	.AP	307	368627
0.000	UDP	24.28.89.160:63319	192.168.192.83:58359		1	42
0.000	TCP	63.208.197.21:443	192.168.192.106:1031	.AP	1	73
0.093	TCP	192.168.193.58:1302	192.168.192.5:110	.AP.SF	8	356
0.093	TCP	192.168.192.5:110	192.168.193.58:1302	.AP.SF	8	440
0.000	UDP	85.160.81.10:6766	192.168.192.217:11084		1	45
0.000	UDP	192.168.192.217:11084	85.160.81.10:6766		1	45
0.000	TCP	192.168.19.247:1723	192.168.60.19:1042	.AP	1	56

Anomaly Detection Methods: MINDS



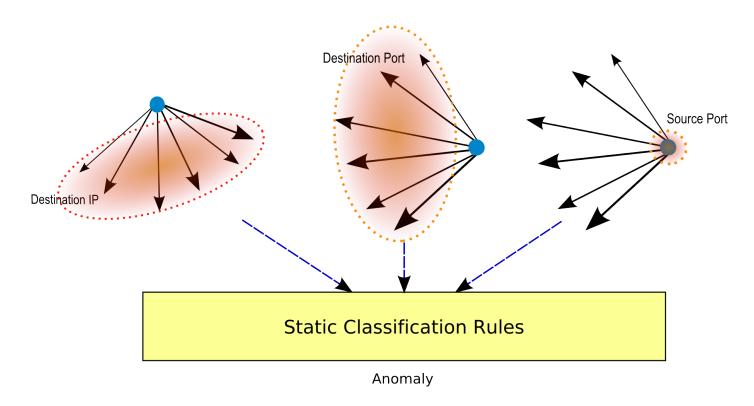


- Source IP
 - Features: Flow counts from/to important IP/port combinations.
 - Classification: Comparison with windowed average of past values, different from original MINDS.

Anomaly Detection Methods: Xu et al.



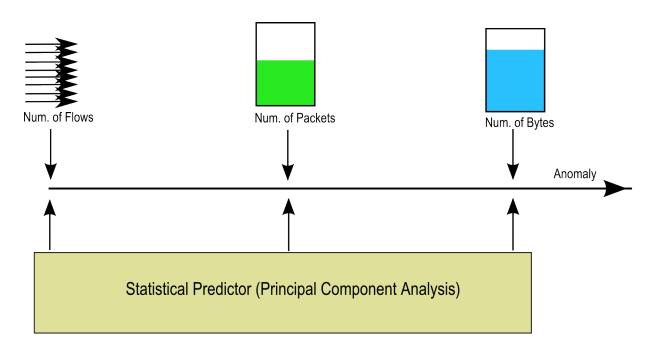
- Features: Determines the entropies of dstIP, dstPrt and srcPrt on the set of all flows from each source IP.
- Classification: Classifies the traffic with a set of static rules.
- All flows from the same source share the classification features and result.



Anomaly Detection Methods: Volume Prediction, Lakhina et al.



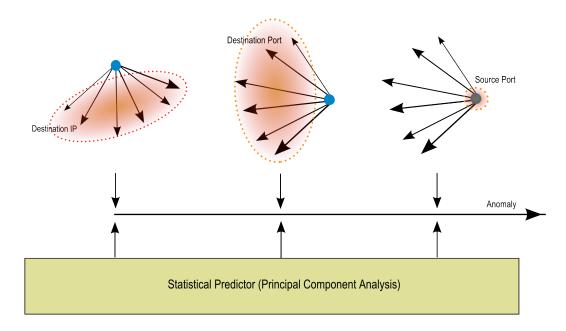
- Uses Principal Component Analysis to predict the volume of traffic from individual sources.
- Features: Ratio of predicted/observed numbers of bytes, packets and flows.
- Classification: Anomaly is derived from the ratio of prediction and observation, for all flows from the same source.



Anomaly Detection Methods: Entropy Prediction, Lakhina et al.



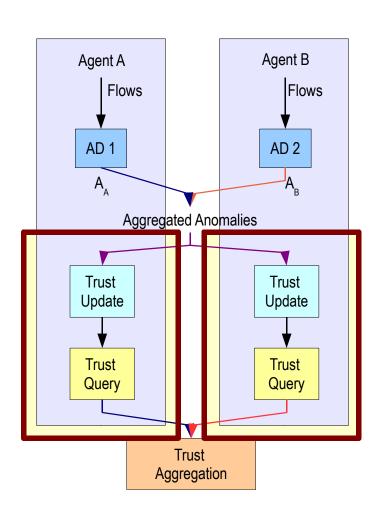
- Uses Principal Component Analysis to predict the entropies of features on the flows from each source IP.
- Features: Difference between the predicted and observed entropies of dstIP, dstPrt and srcPrt on the set of all flows from each source IP.
- Classification: Anomaly is derived from the difference between the prediction and observation, defined by the source only.



Extended Trust Modeling



- Agents describe each flow using its identity and context.
- Identity defined by the features measured on the flow
- Context uses the features from the AD model, measured on other flows
- Metric feature space, metrics determines similarity
- Trustfulness is determined for cluster
 centroids in the feature space



Extended Trust Modeling: Identity/Context Example



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Identity

■ srcIP: 192.168.195.164

■ dstIP: 192.168.10.12

■ srcPrt:1086

■ dstPrt: 445

protocol: TCP

■ bytes: 84

packets: 2

Context (MINDS)

count-srcIP: 3

count-dstIP: 1

count-srcIP-dstPrt:2

■ count-dstIP-srcPrt:1

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■ srcPrt:1086

■ dstPrt: 445

protocol: TCP

■ bytes: 84

packets: 2

Context (MINDS)

count-srcIP: 3

■ count-dstIP: 1

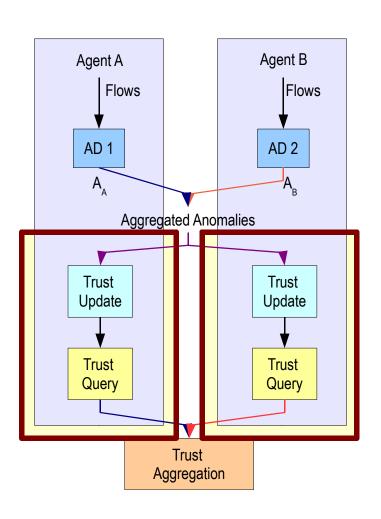
count-srcIP-dstPrt:2

count-dstIP-srcPrt:1

Extended Trust Modeling

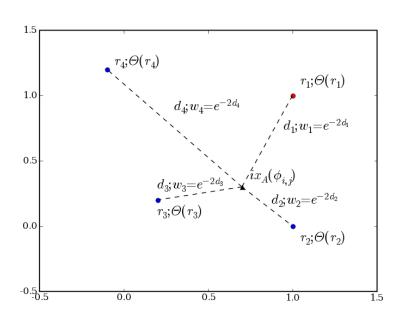


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Trust Update and Query



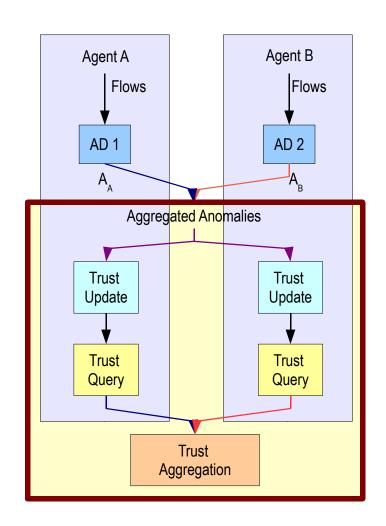


Trustfulness update:

- 1. Find **relevant** centroids
- 2. Determine the update **weight** for each centroid
- 3. **Update** the trustfulness of centroid using a given weight
- Trustfulness query:
 - 1. Find relevant centroids
 - 2. Determine the **weight** for each centroid
 - 3. **Aggregate** the trustfulness from centroid, with respective weights

Multi-Source Trustfulness Integration



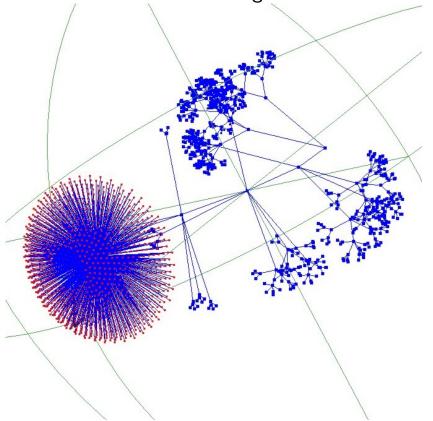


- Effectiveness improved by:
- Aggregated anomaly value reduces the effect of singular anomaly peaks
- Similarity between flows varies between the agents e.g. trustfulness is based on anomaly aggregated over the agentspecific clusters
- Normalized individual trustfulness is reaggregated into the common value

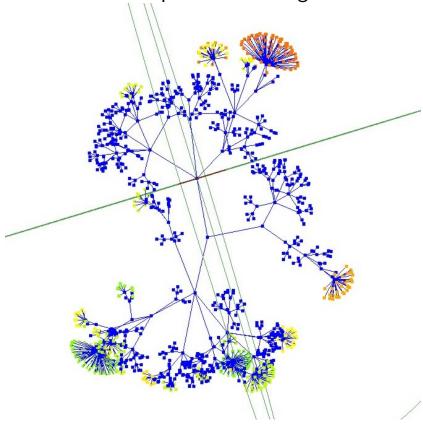
Agent Specific Clusters



Attack data (as identified by other agent) are concentrated in a single centroid.

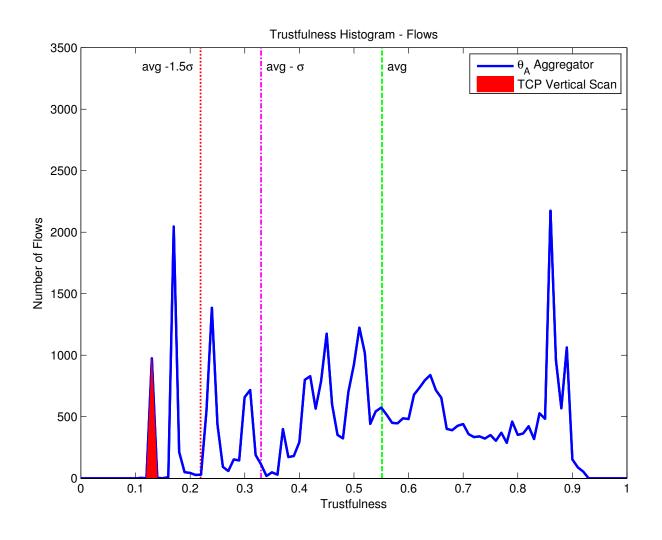


False positive data are spread across the whole feature space of other agent.



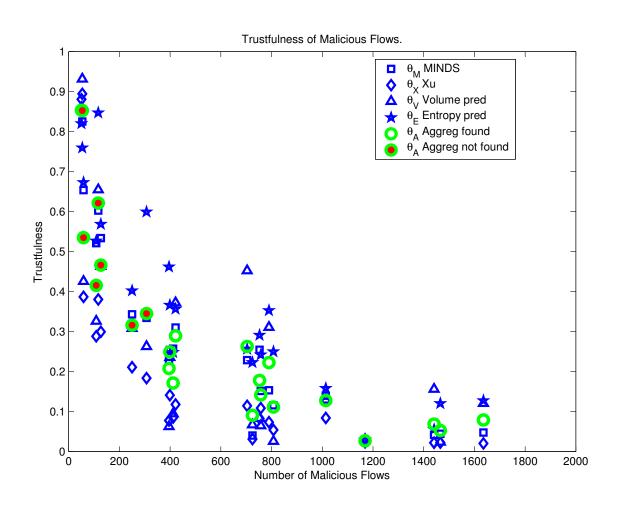
System Output





Known Attacks, Regardless of Type





Third Party Attacks Results

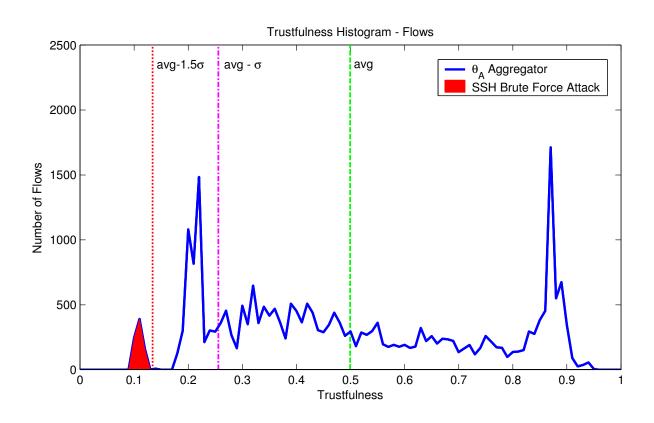


Anomalous		$A_{\mathcal{M}}$	$A_{\mathcal{X}}$	$A_{\mathcal{E}}$	$A_{\mathcal{V}}$	$A_{\mathbb{M}}$
	detected	6653	3246	13541	12375	9911
# flows	TP	35	168	5841	5868	4709
	FP	6618	3078	7700	6507	5202
	FP[%] all traffic	15.9 %	7.4 %	18.5 %	15.6 %	12.5 %
	detected	72.5	322.3	17.2	16.7	12.5
# srcIP	TP	1.7	0.2	2.5	2.7	2.3
	FP	70.8	322.1	14.7	14.0	10.2
	FP[%] all traffic	1.52 %	6.94 %	0.31 %	0.30 %	0.22 %

Untrusted		Θ_M	Θ_X	Θ_E	Θ_V	Θ
	detected	9149	9975	10704	9518	9741
# flows	TP	5242	5712	5833	5864	5769
	FP	3907	4263	4872	3654	3972
	FP[%] all traffic	9.4 %	10.2 %	11.7 %	8.8 %	9.5 %
	detected	7.8	11.3	13.5	10.8	6.7
# srcIP	TP	2.7	2.7	2.3	2.7	2.7
	FP	5.1 0.11 %	8.6	11.2	8.1	4.0
	FP[%] all traffic		0.19 %	0.24 %	0.18 %	0.09 %

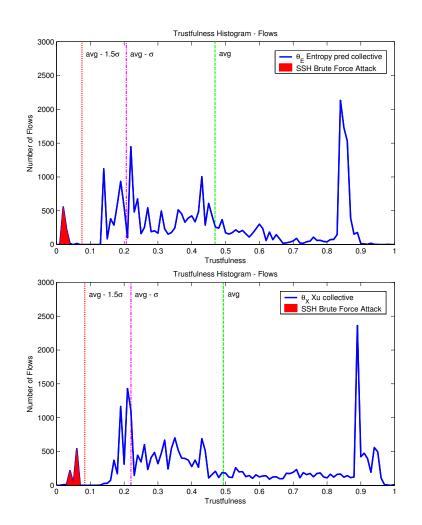
Impact of Collaboration 1

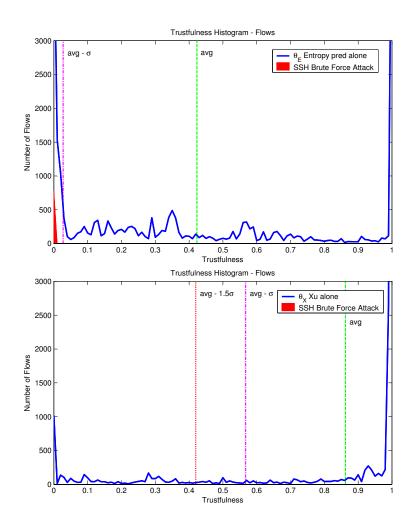




Impact of Collaboration 2

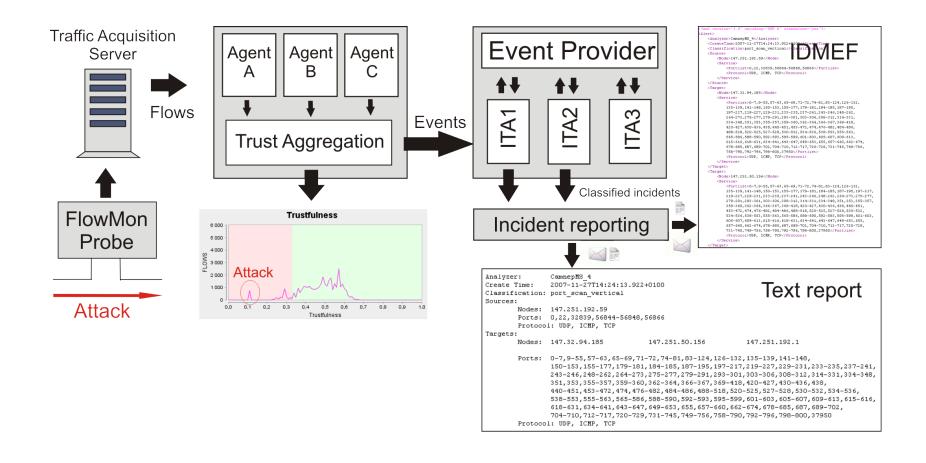






Reporting





Conclusions



- Collaborative trust mechanism reduces the error rate of existing anomaly detection approaches.
- The error rate reduction is achieved by:
 - Aggregation of anomaly values
 - Specific trust models of individual agents, each providing different insight into the flow data
 - Trustfulness aggregation re-integrates the opinions from the various trust models, each using different perspective
- Agent-based trust techniques can be used under high-performance constraints.
- A-Globe multi-agent platform has negligible computational overhead, architecture naturally scales to multiprocessor environments.



Thank You For Your Attention