

# ADSICS

## Anomaly Detection System for Industrial Control Systems

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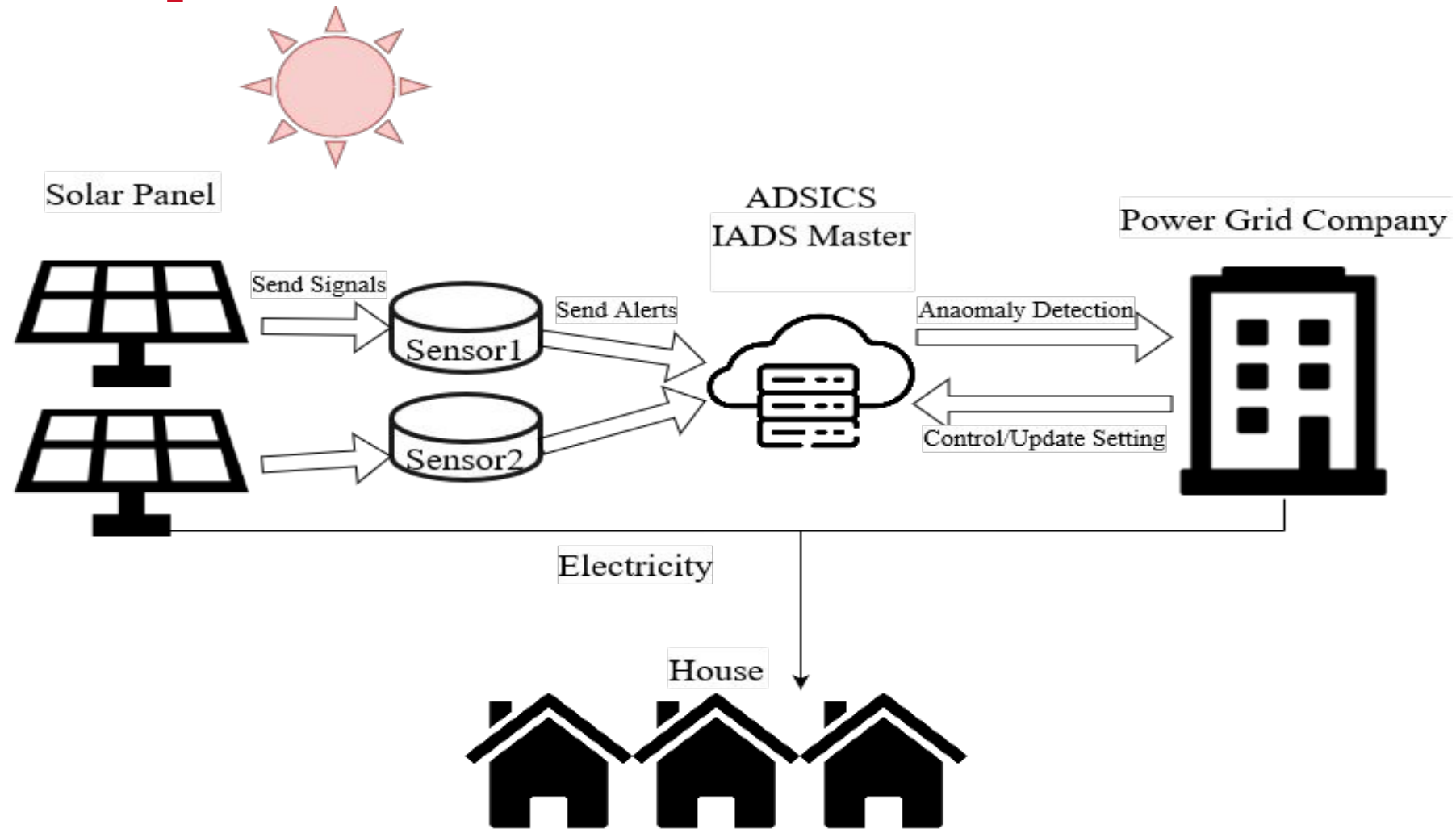
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Advisors : Dr. Manimaran Govindarasu, Moataz Abdelkhalek

# Problem Statement

- Attacks on power distribution companies are now more common due to the increased use of IoT devices and the lack of security on power grid systems.
- ADSICS is a surveillance program that detects and prevents cyber attacks using anomaly detection.

# Conceptual Sketch



# Requirements & Constraints

## Functional Requirements:

- Use machine learning to detect network anomalies
- Verify incoming alerts and discard false positives
- Display alerts for easy human understanding
- Present temporal and spatial details for each alert

## Non-Functional Requirements:

- Alerts should be presented intuitively
- Alerts should be received within 10ms
- The system should be able to handle a large volume of alerts
- The system should be reliable and maintain uptime continuously

## Constraints:

- The anomaly detection must use SecurityOnion tools (specifically Elasticsearch)

# Standards

<b>Standard</b>	<b>Application</b>	<b>Justification</b>
<b>IEEE 692-2013</b>	IADS SENSOR IADS MASTER	Addresses cybersecurity and control related equipment requirements for threat assessment.
<b>ISO IEC 27039-2015</b>	IADS MASTER	Provides guidelines for selection, deployment, and operations of intrusion detection system detection and prevention systems.
<b>ISO/IEC 27017:2015</b>	CLOUD SERVER	Provides guidance on the information security aspects of cloud computing, recommending the implementation of cloud-specific information security controls that supplement the guidance of the <b>ISO/IEC 27002</b> and <b>ISO/IEC 27001</b> standards.
<b>IEEE 1711.2-2019</b>	IADS SENSOR	Protects communication of intelligent devices in the power industry.
<b>IEEE 802</b>	IADS SENSOR	Describes recommended practices for communication over various types of networks, such as wireless networks.

# Market Survey

- Previous work by client - D-IDS for Cyber-Physical DER Modbus System
- Datasets: KDD, IDS, NSL+KDD, IoT23
- Anomaly detection algorithms:
  - Decision Tree
  - Random Forest
  - K-Nearest Neighbor
  - Support Vector Machine
  - Deep Neural Network

# System Architecture

## Functional Decomposition:

IADS Sensor, IADS Master

## Operating System:

Kali Linux, Linux(SO), and Windows XP

## Software Architecture:

- vSphere - virtual machine
- SecurityOnion
  - ElasticSearch - machine learning
  - Kibana - visualization
  - SNORT - filtering



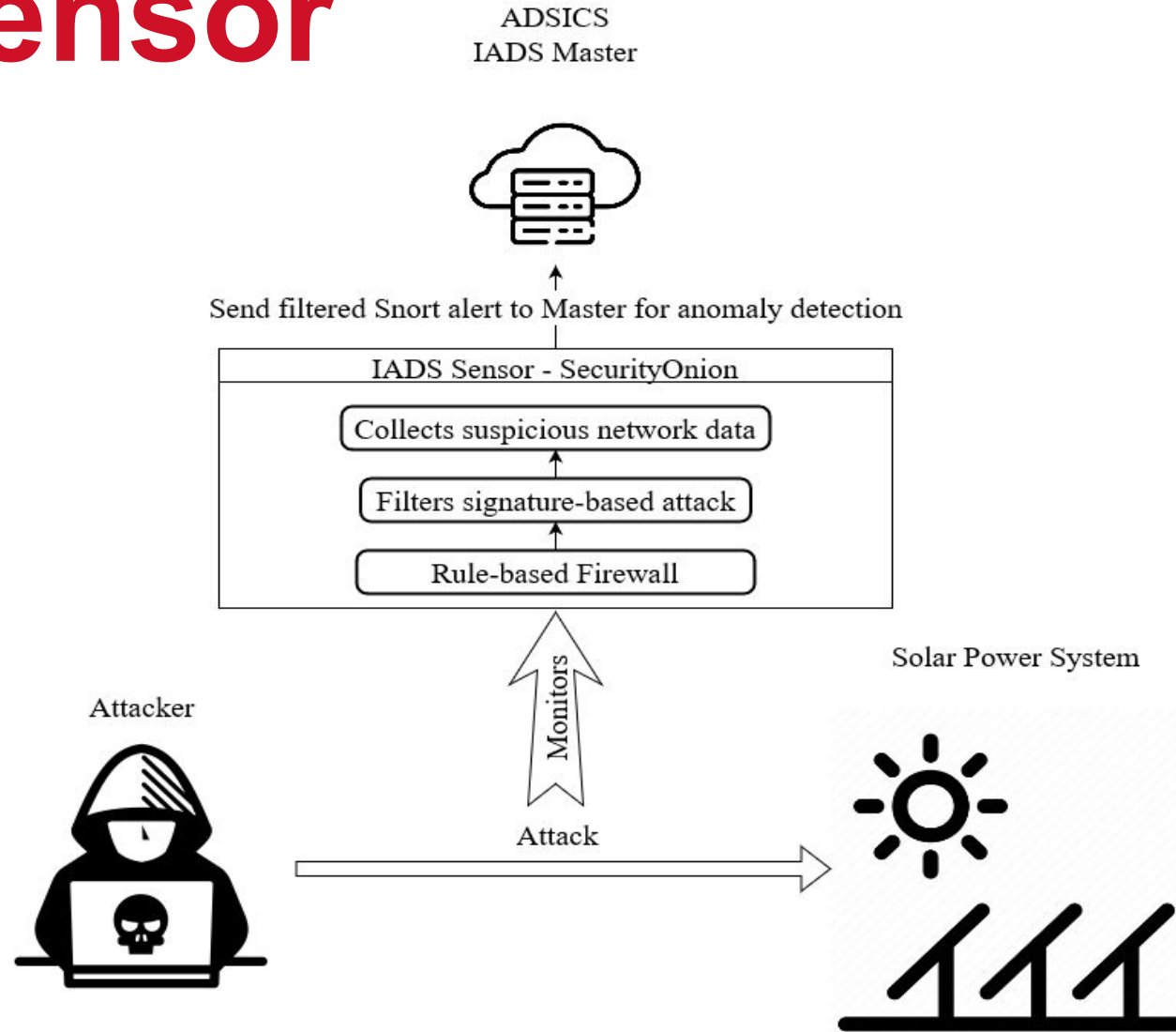
elastic



kibana

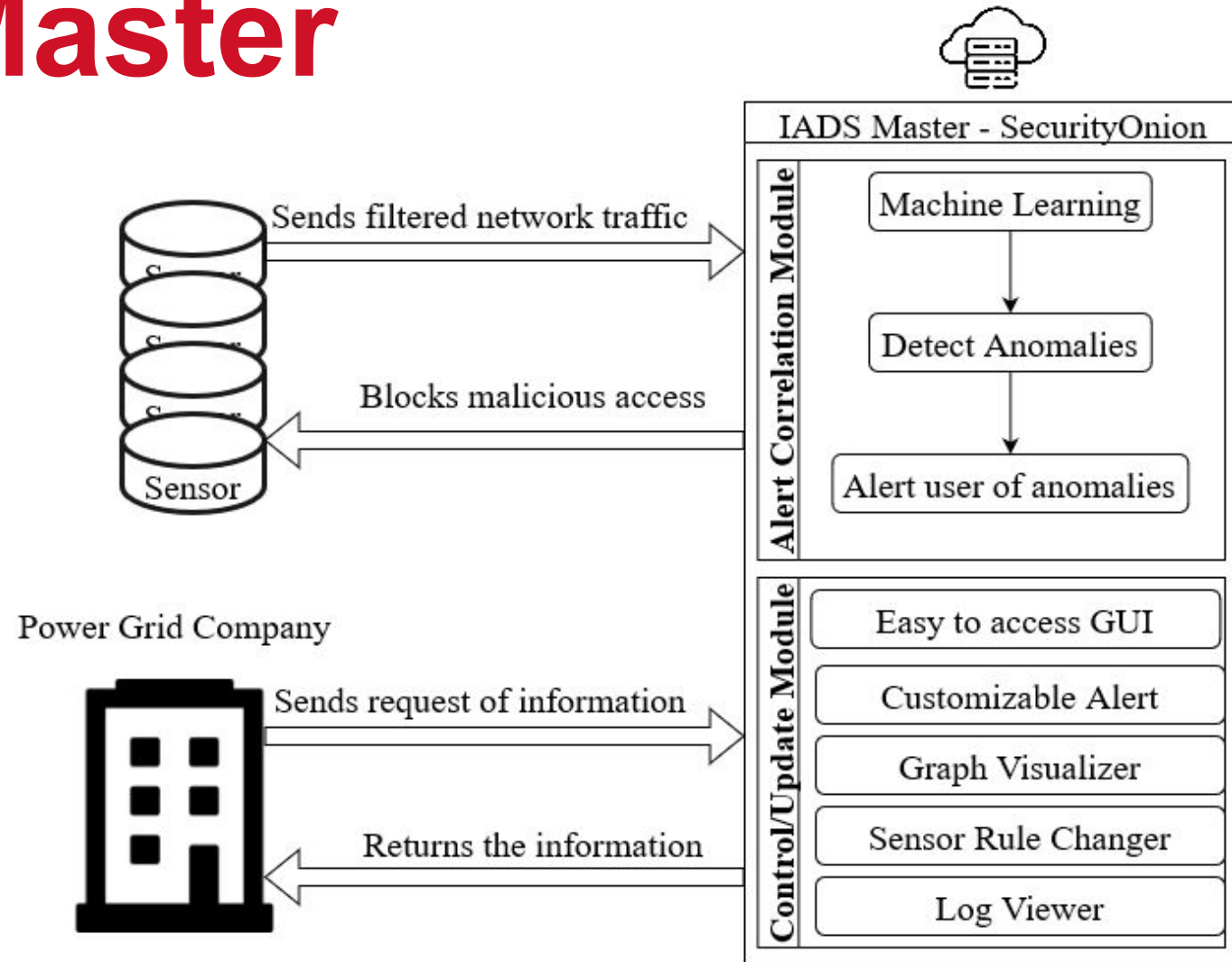


# IADS Sensor



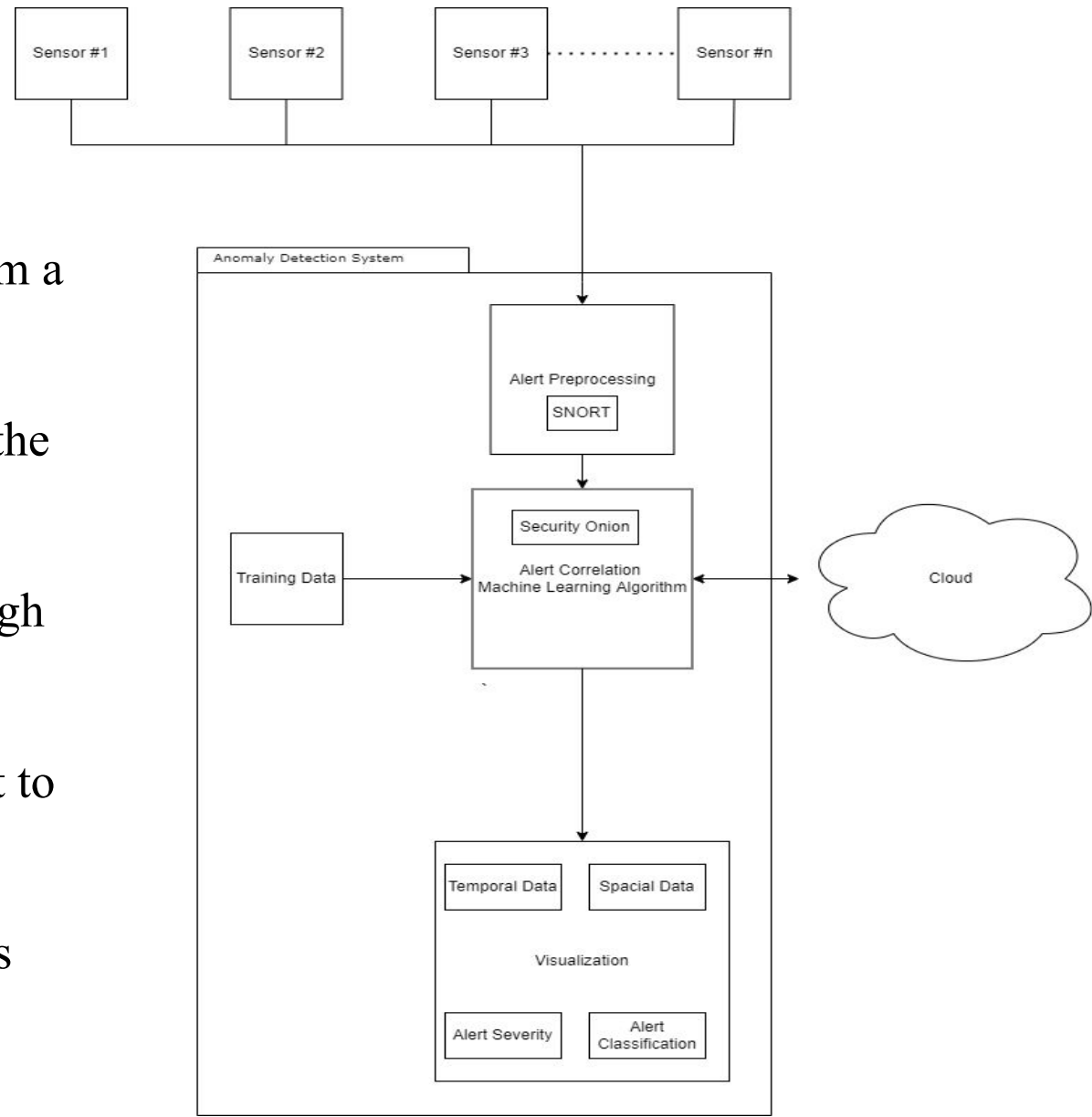


# IADS Master

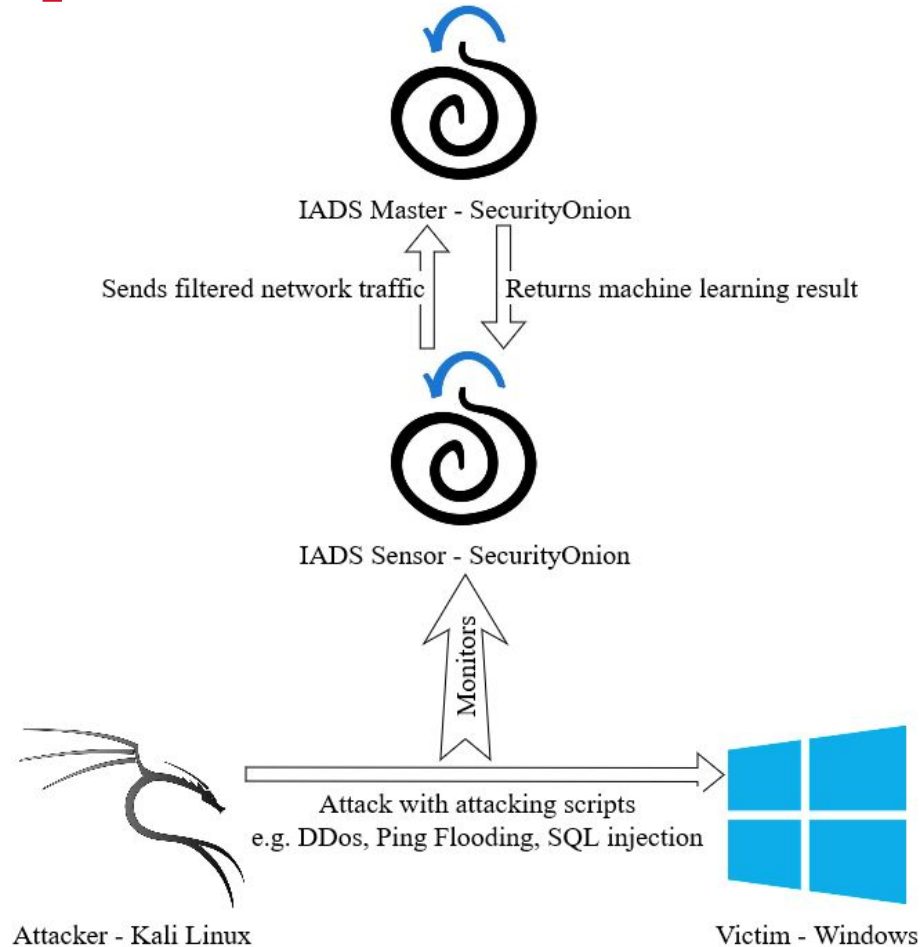
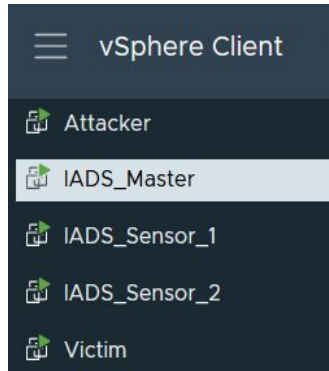


# Detailed Diagram

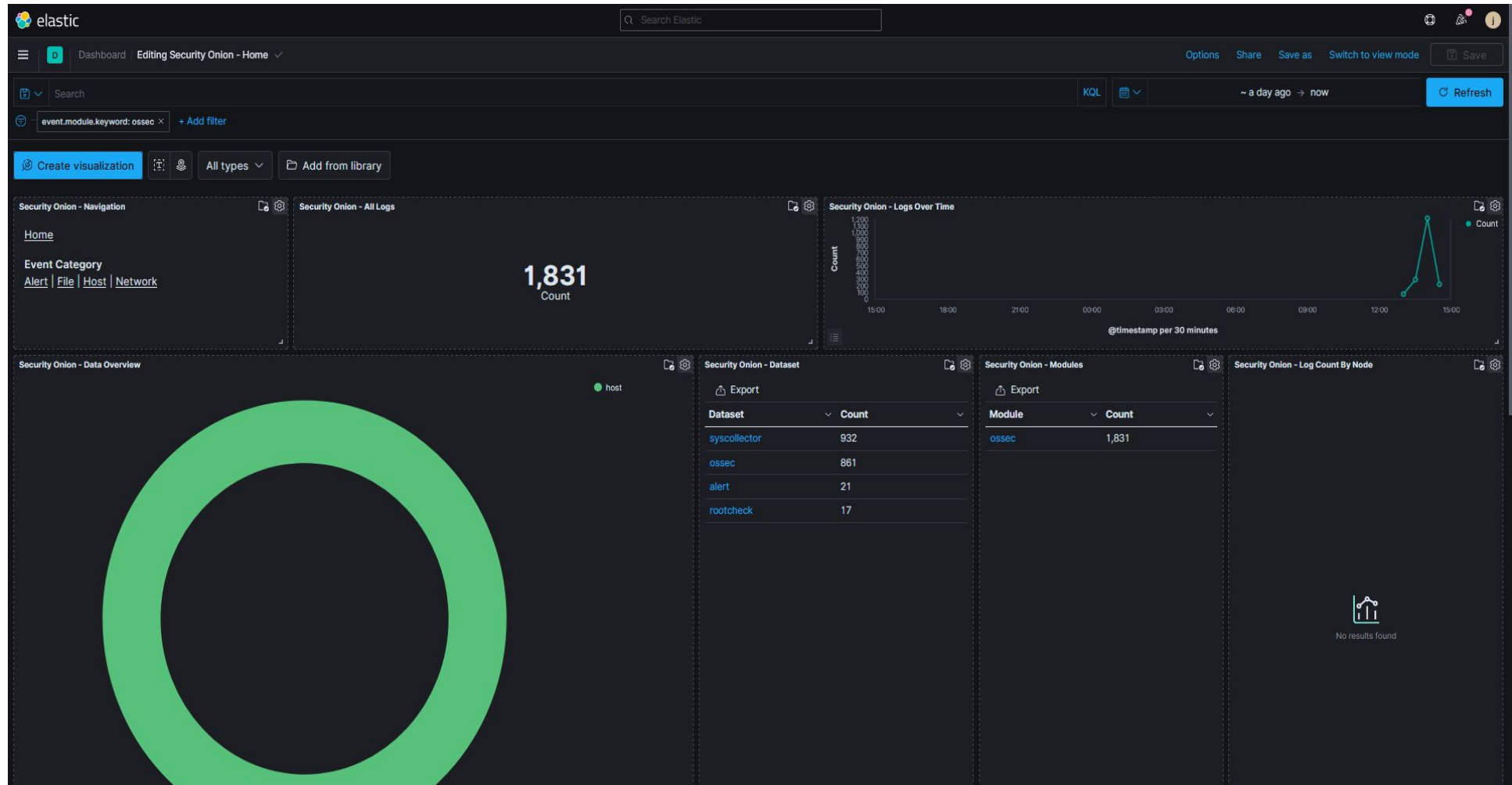
- Our design accepts many alerts as input, originating from a variety of sensors
- These alerts will be processed, ensuring that they enter the anomaly detection system
- Then, our algorithm will perform alert correlation through the Cloud
- Our machine learning model will be trained by a dataset to draw relationships between alerts
- The conclusions will then be visualized for user analysis



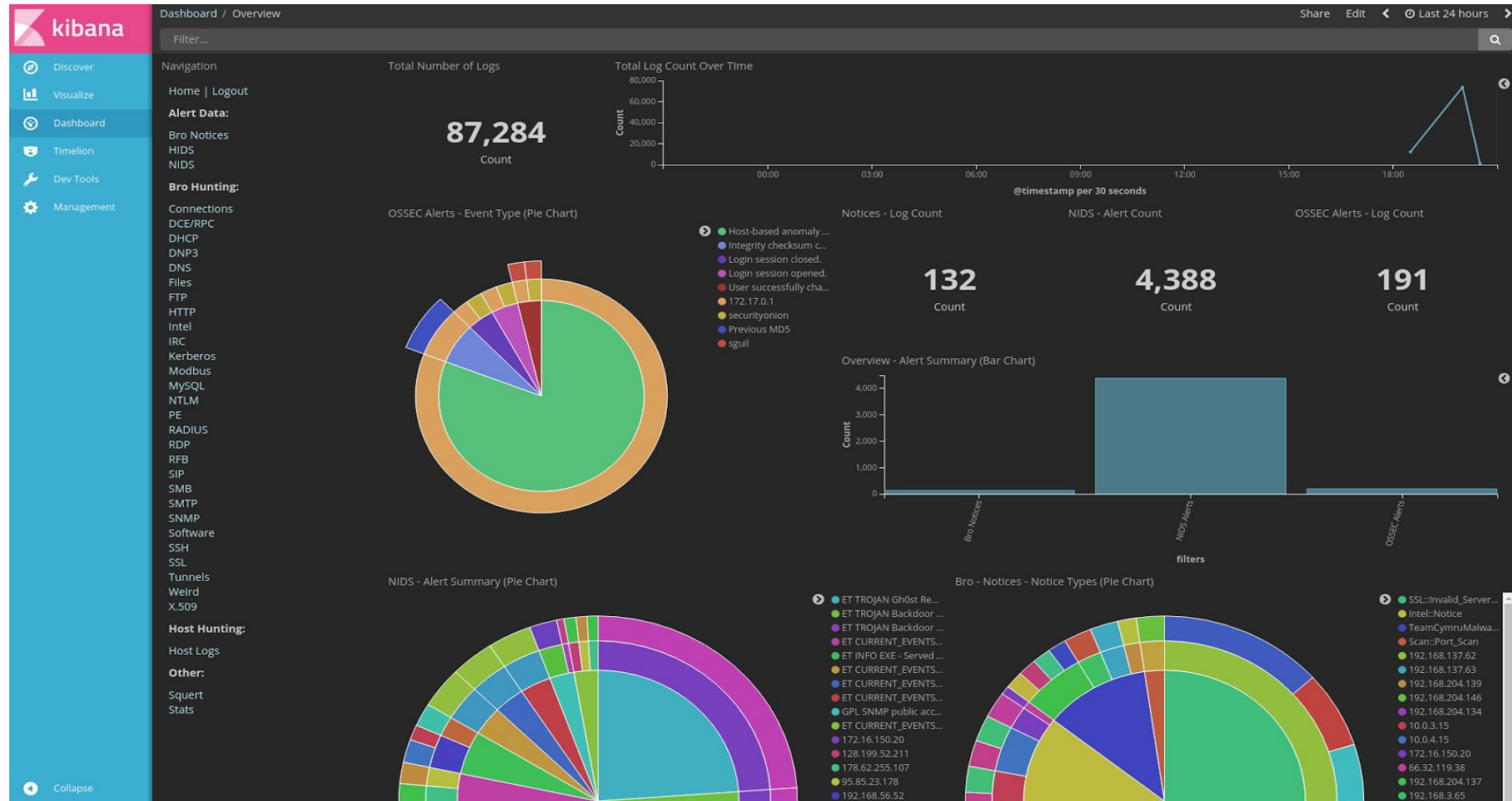
# Prototype Implementations



# IADS Master Dashboard



# Visualizing Alerts in Kibana



<https://blog.securityonion.net/2017/06/towards-elastic-on-security-onion.html>

# NSL - KDD Dataset

No.	Feature Name	No.	Feature Name
1	Duration	22	is_guest_login
2	protocol type	23	<b>count</b>
3	service	24	srv_count
4	<b>flag</b>	25	<b>serror_rate</b>
5	src_bytes	26	<b>srv_serror_rate</b>
6	<b>dst_bytes</b>	27	<b>rerror_rate</b>
7	land	28	srv_rerror_rate
8	wrong_fragment	29	<b>same_srv_rate</b>
9	urgent	30	diff_srv_rate
10	hot	31	srv_diff_host_rate
11	num_failed_logins	32	dst_host_count
12	logged_in	33	<b>dst_host_srv_count</b>
13	num_compromised	34	dst_host_same_srv_rate
14	root_shell	35	dst_host_diff_srv_rate
15	su_attempted	36	dst_host_same_src_port_rate
16	num_root	37	dst_host_srv_diff_host_rate
17	num_file_creations	38	<b>dst_host_serror_rate</b>
18	num_shells	39	<b>dst_host_srv_serror_rate</b>
19	num_access_files	40	dst_host_rerror_rate
20	num_outbound_cmds	41	dst_host_srv_rerror_rate
21	is_host_login	42	<b>Classification of the data</b>

Dataset	Number of Records:					
	Total	Normal	DoS	Probe	U2R	R2L
KDDTrain+20%	25192	13449 (53%)	9234 (37%)	2289 (9.16%)	11 (0.04%)	209 (0.8%)

Training Dataset		
Category	KDDTrain+_20Percent	
	Attack	Count
Normal	normal	13,449
<b>Subtotal</b>		<b>13,449</b>
Probe	ipsweep	710
	satan	691
	portsweep	587
	nmap	301
<b>Subtotal</b>		<b>2289</b>
DoS	neptune	8282
	smurf	529
	back	196
	teardrop	188
	pod	38
	land	1
<b>Subtotal</b>		<b>9234</b>
U2R	buffer_overflow	6
	rootkit	4
	loadmodule	1
<b>Subtotal</b>		<b>11</b>
R2L	guess_passwd	10
	warezmaster	7
	imap	5
	multihop	2
	phf	2
	ftp_write	1
	spy	1
	warezclient	181
<b>Subtotal</b>		<b>209</b>
<b>Total</b>		<b>25,192</b>

Job status docs evaluated

**stopped** **25192**

**Normalized confusion matrix for entire dataset** [🔗](#)

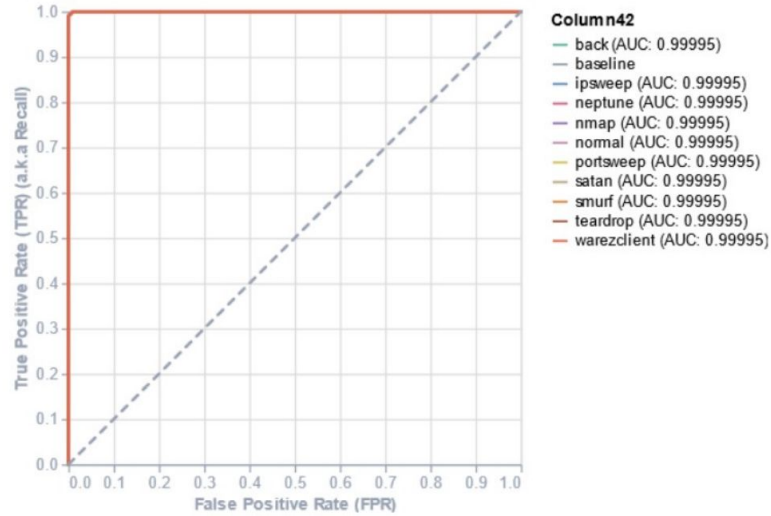
Predicted class

Columns		back	ipsweep	neptune	nmap	normal	portsweep	4 more
Actual class								
back		100%	0%	0%	0%	0%	0%	0%
ipsweep		0%	100%	0%	0%	0%	0%	0%
neptune		0%	0%	100%	0%	0%	0%	0%
nmap		0%	0%	0%	100%	0%	0%	0%
normal		0%	0%	0%	0%	100%	0%	0%
portsweep		0%	0%	0%	0%	0%	100%	0%

**Evaluation quality metrics**

**0.999** **0.948**  
 Overall accuracy [?](#) Mean recall [?](#)

**Receiver operating characteristic (ROC) curve** [🔗](#)



# Testing and Evaluation

- Testing is performed on the actual platform (Client VM)
- Functional testing
  - JUnit, Mockito - UI testing
  - Visualization testing
- Security evaluation
  - Black box testing - Low false positive, false negative rate
- Timing evaluation
  - Real-time operation



# Design Complexity

- Our design required understanding of advanced technical concepts such as anomaly detection, network intrusion, and machine learning algorithms. Since none of us had any background in cybersecurity, this caused us to spend an unexpected amount of time conducting background research.
  - The required testbed environment was unreliable.
- Design iterations needed:
  - Local implementation vs testbed implementation
  - Datasets
  - Algorithms
  - Single Sensor

# Project Plan – Milestones

- Filter and track alerts through spatial and temporal data
- Accept continuous alerts from the sensor VMs
- Build a UI to display tracked anomaly data intuitively
- Process every alerts in 10 ms delay for real time operation
- Eliminate false positives with 90% accuracy



# Conclusion

We aim to use a machine learning algorithm within our VM to process alerts, ensuring that they contain all the necessary information such as time, location, severity, and type to be analyzed by a user. We will go into the future of this project with the ultimate goal of designing a user experience that emphasizes accuracy, speed, and utility.

**Thank You For Your Time!**  
**Any Questions?**

# References

Slide 13 Image

<https://blog.securityonion.net/2017/06/towards-elastic-on-security-onion.html>