

Unsupervised Real-Time Network Intrusion and Anomaly Detection by Memristor Based Autoencoder

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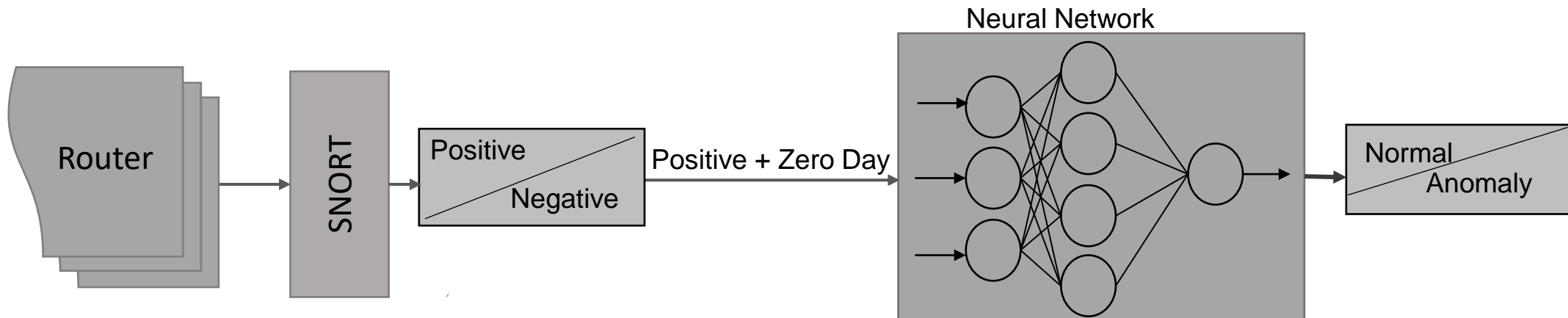
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Outline

- Introduction
- Anomaly Detection Methods and Applications
- Motivation and Challenges
- Proposed Anomaly Detection System
- Results of Intrusion and Anomaly Detection System
- Summary
- Future work

Introduction

- Network Intrusion
- Intrusion Detection system
- SNORT
- What if new unknown packet comes?
E.g. 'Zero Day'



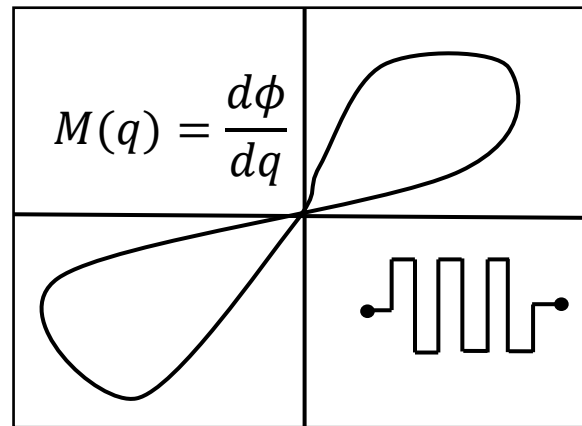
Block diagram of the neural network based intrusion detection system

Introduction (Contd.)

Deep Learning Vs Power Consumption



Deep Learning for IoTs and Edge Devices



Memristor

- Memristive system could be a solution

Anomaly Detection Methods and Applications

What are the anomalies?

- Abnormalities/outliers

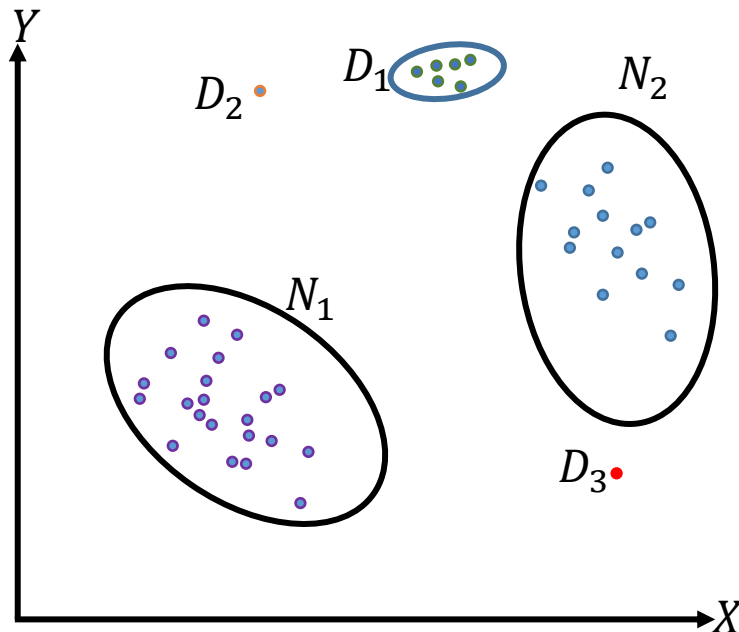


Illustration of anomalies in two-dimensional data set

Anomaly detection Methods:

- Unsupervised (AE, GAN, RNN, LSTM etc)
- Supervised (DNN, CNN)
- Hybrid model (AE+SVM)
- One-Class Neural Network

Applications:

- Cyber-Intrusion Detection
- Malware Detection
- Internet of Things (IoTs) Big Data Anomaly Detection
- Fraud Detection
- Medical Anomaly Detection
- Industrial Damage Detection

Motivation and Challenges

Motivation:

- Deep learning implementation for IoTs and edge devices
- Detection and learning of anomalies in real-time

Challenges:

- Boundary between normal and malicious is not explicitly defined
- Continual learning and the catastrophic forgetting

Our Contribution

- Design and implementation of unsupervised autoencoder in memristor crossbar devices
- Develop autoencoder training in memristor device
- Proposed an online learning system for network anomaly detection

Dataset Preprocessing

- NSL-KDD network dataset ← KDD Cup'99 dataset
- Training data has 125,973 packets, 23 different data types
- 43 attributes, consists numerical and alphanumeric data
- Preprocessed and sorted out the packets
- Network is pretrained with 90% of Normal
- Tested with 10% normal and 10% of total malicious data

Normal Packet

```
0,tcp,ftp_data,SF,491,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,2,2,0,0,0,0,1,0,0,150,25,0.17,0.03,0.17,0,0,0,0,0.05,0,normal,20
```

Malicious Packet

```
0,tcp,ftp_data,SF,334,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,2,2,0,0,0,0,1,0,0,2,20,1,0,1,0.20,0,0,0,0,warezclient,15
```

Preprocessed Malicious Packet

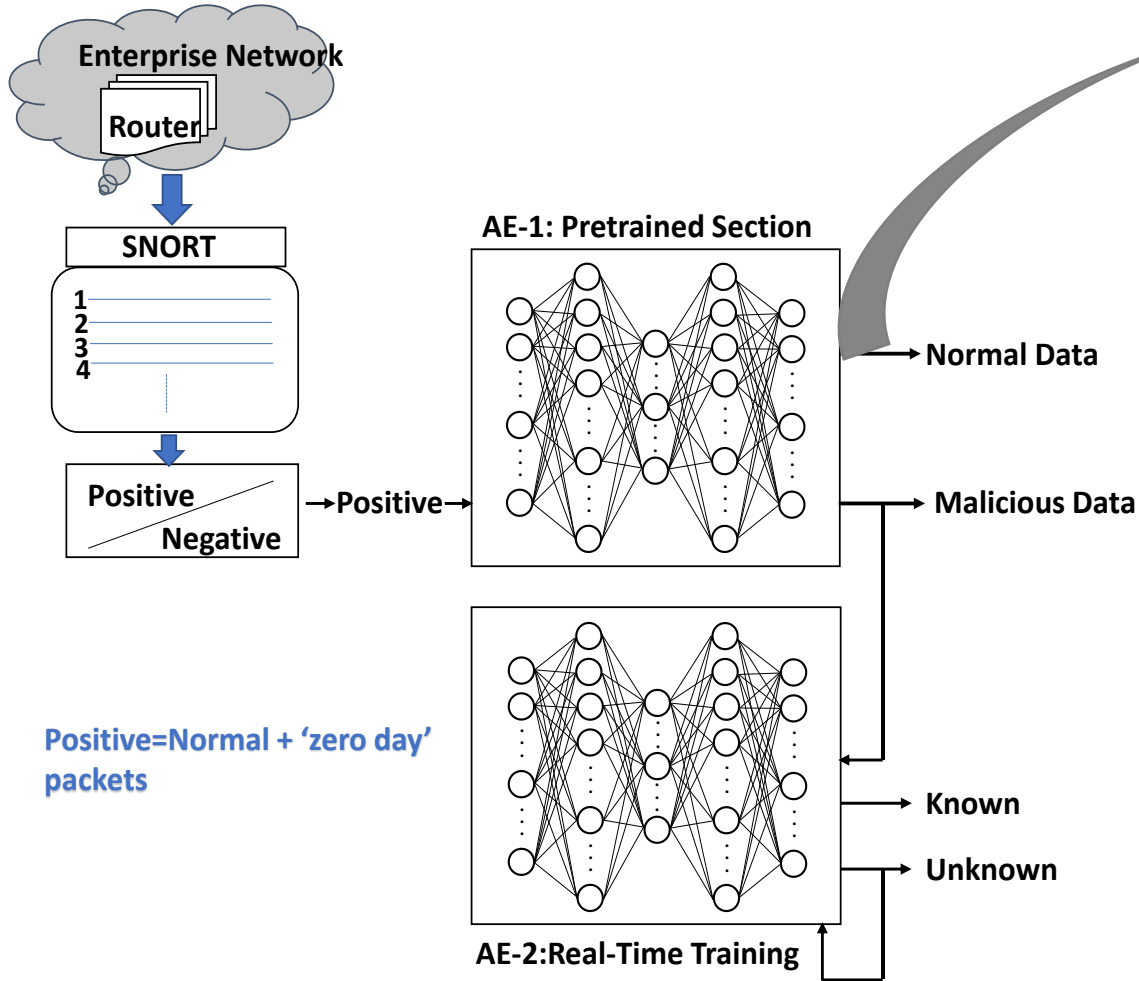
```
0,0.5,0.188,0.629,3.55e-7,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0.00391,0.00391,0,0,0,0,1,0,0,0.588,0.098,0.17,0.03,0.17,0,0,0,0.05,0,0,0.9523
```

Preprocessed Malicious Packet

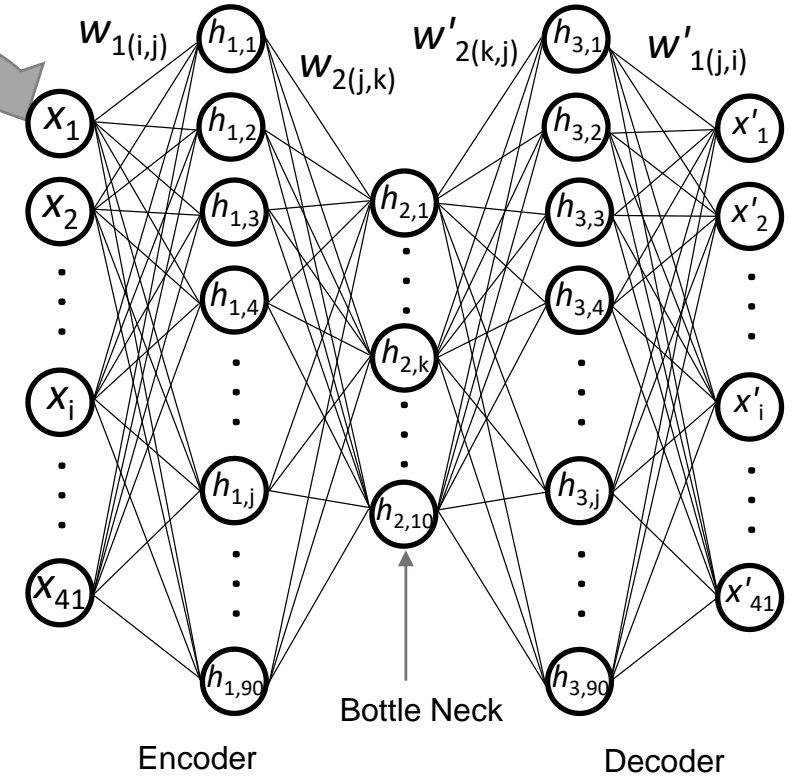
```
0,0.5,0.188,0.629,2.42e-7,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0.00391,0.0039,0,0,0,0,1,0,0,0.0078,0.078,1,0,1,0.2,0,0,0,1,0.714
```


Proposed Anomaly Detection System

System Prototype Model



Autoencoder (AE) Neural Network

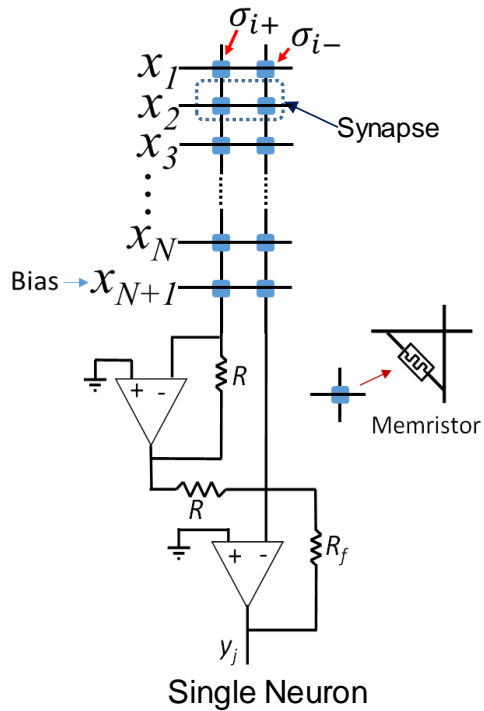


41 → 90 → 10 → 90 → 41

- AE learns to regenerate the input data at output
- AE can reduce the dimension of input data

Intrusion And Anomaly Detection System with AE neural Network

Memristive Neural Network and Crossbar Circuit



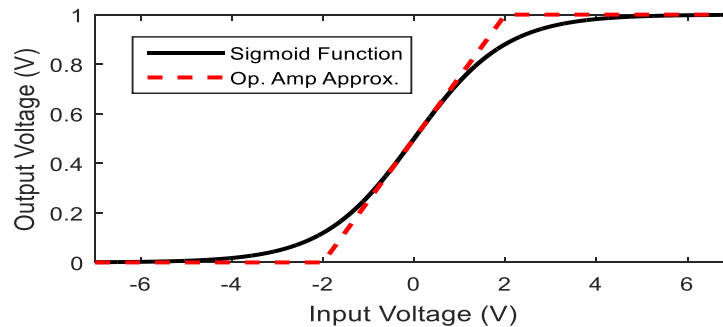
DOT Product:

$$DP_j = \sum_{i=1}^{N+1} x_i \times (\sigma_{ij}^+ - \sigma_{ij}^-) \quad (1)$$

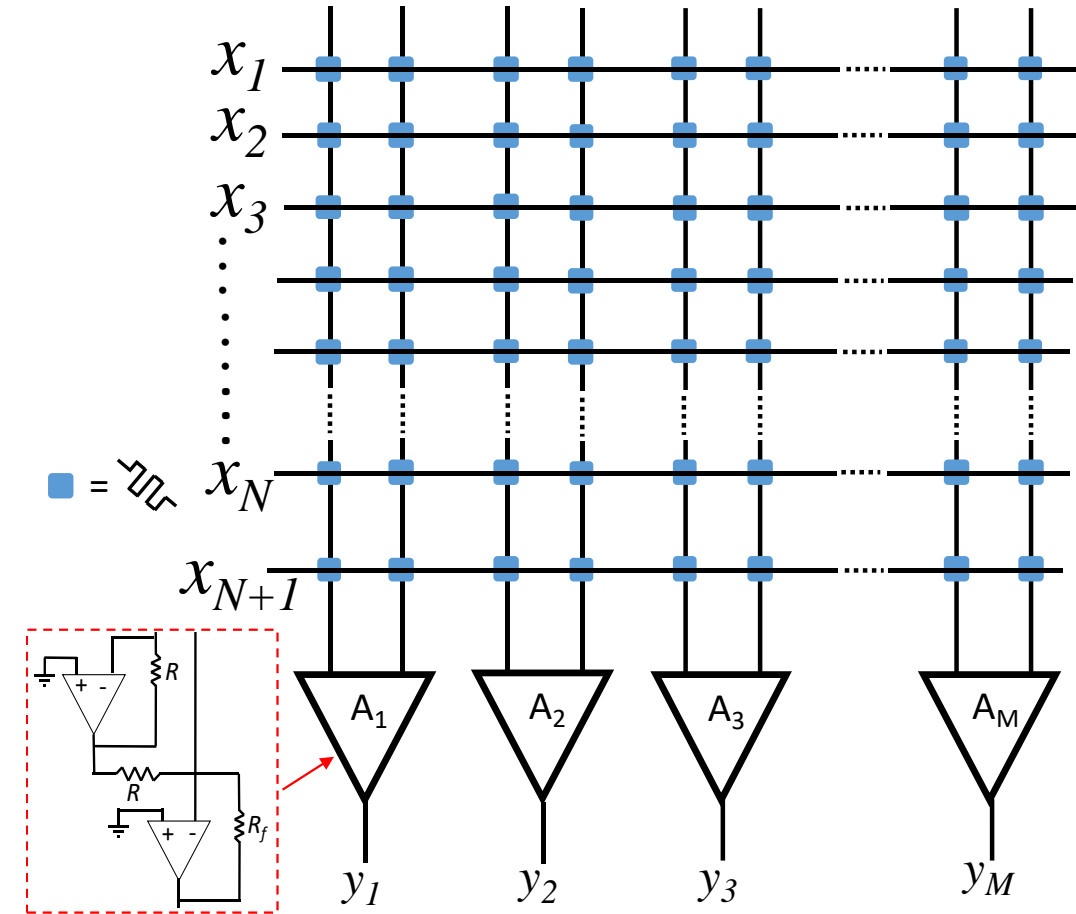
Sigmoid Approximation:

$$f(x) = \frac{1}{1+e^{-x}} \quad (2)$$

$$g(x) = \begin{cases} 1, & x > 2 \\ 0.25x + 0.5, & |x| \leq 2 \\ 0, & x < -2 \end{cases} \quad (3)$$



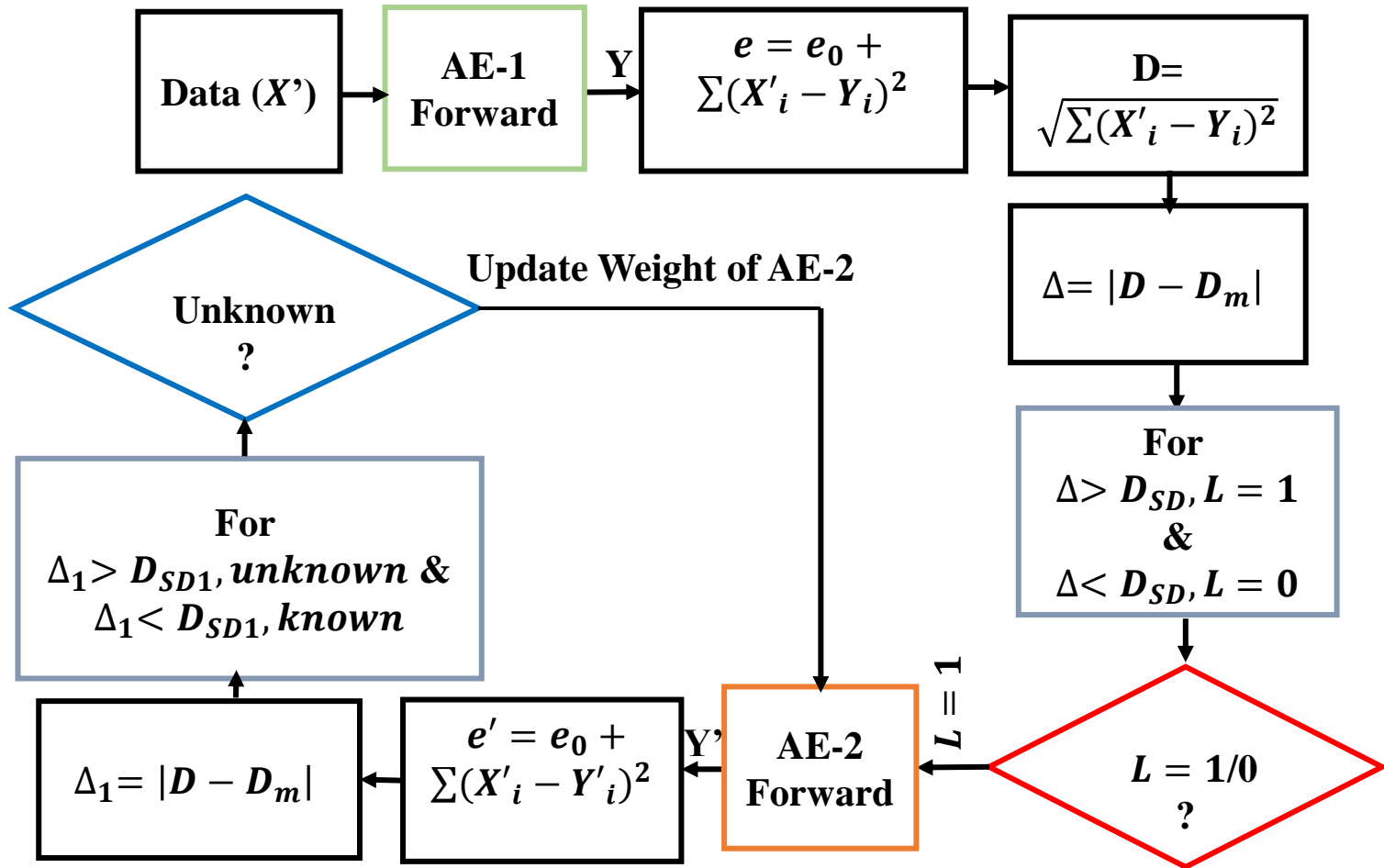
Ideal and approximate Sigmoid Function



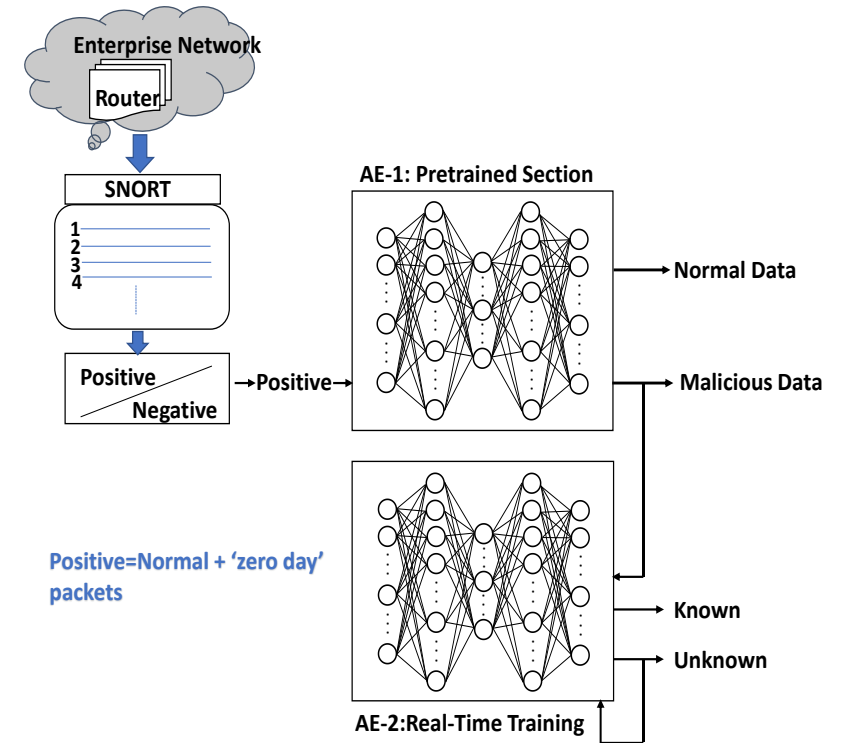
Training of the Network

- apply x_i
- crossbar computes the dot product DP_j
- output signal y_j
- error : $\delta_j = (x_i - y_j)f'(DP_j)$
- backpropagate the error $\delta_j = \sum_k \delta_k w_{k,j}f'(DP_j)$ in each hidden layer
- update the weights according δ_j as $\Delta w_j = \eta \delta_j x$
- calculate $D = \sqrt{\sum (X_i - Y_j)^2}$ and $D_{SD} = \sqrt{\frac{\sum (D - D_m)^2}{N}}$

System Flowchart of Anomaly Detection System

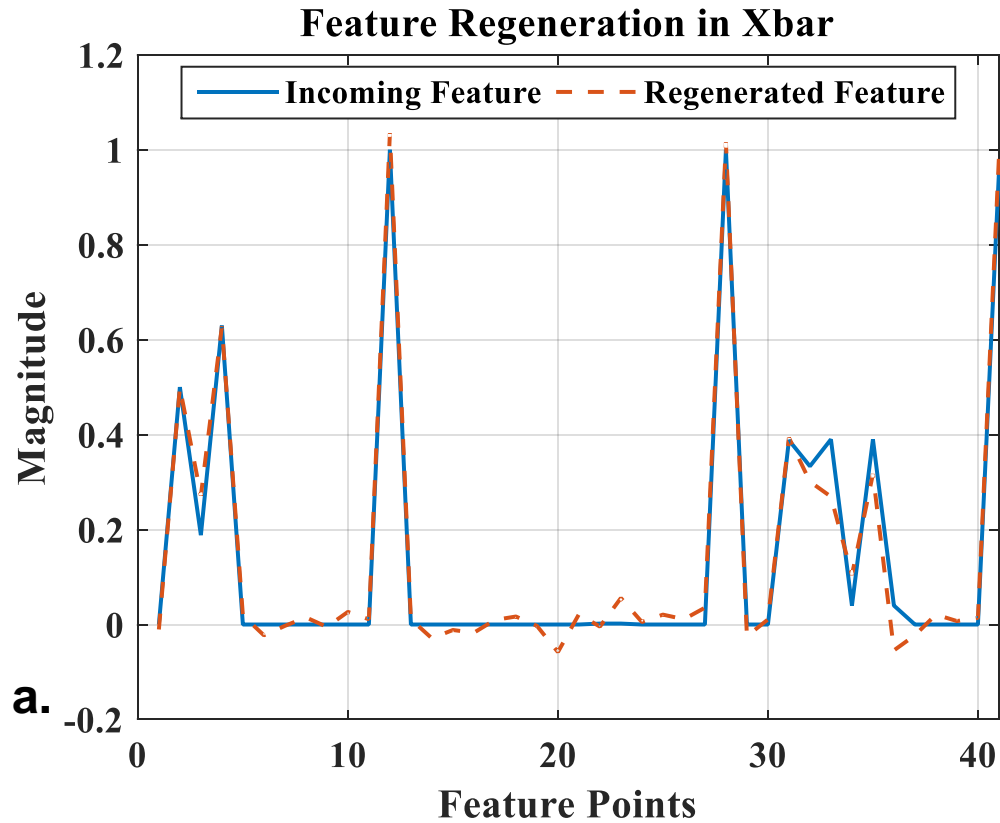


Flowchart of Real-time Anomaly detection System

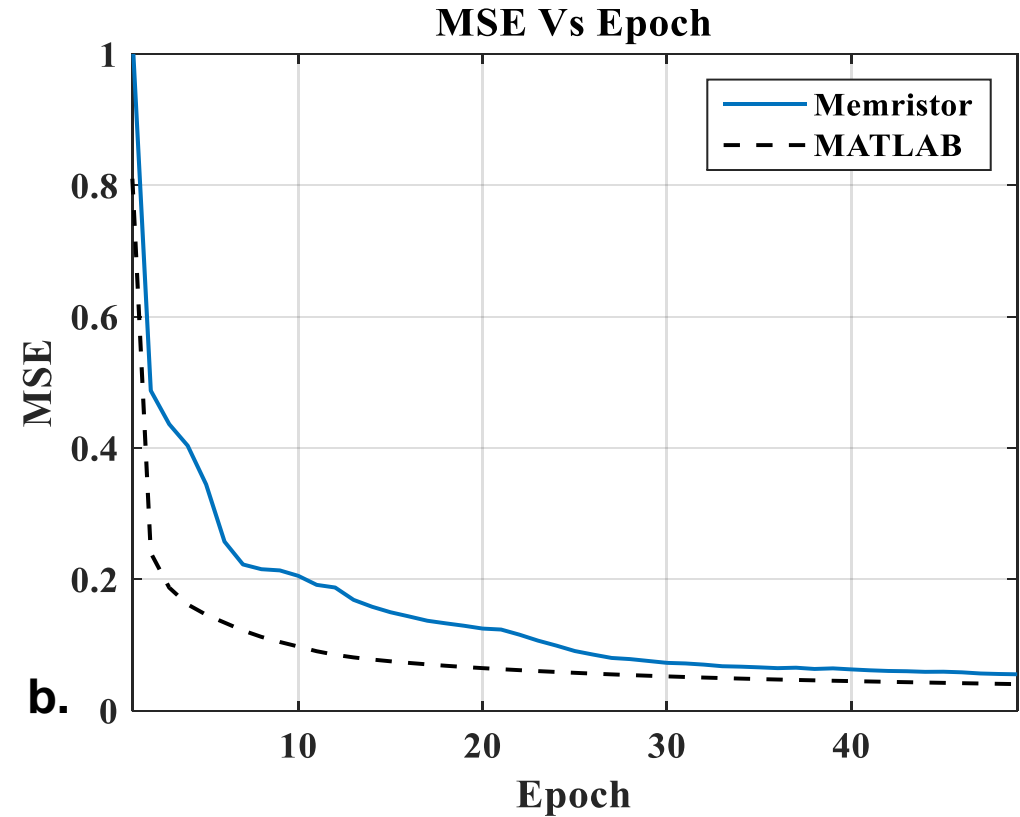


Anomaly Detection System

Pretraining of Autoencoder-1 (AE-1)

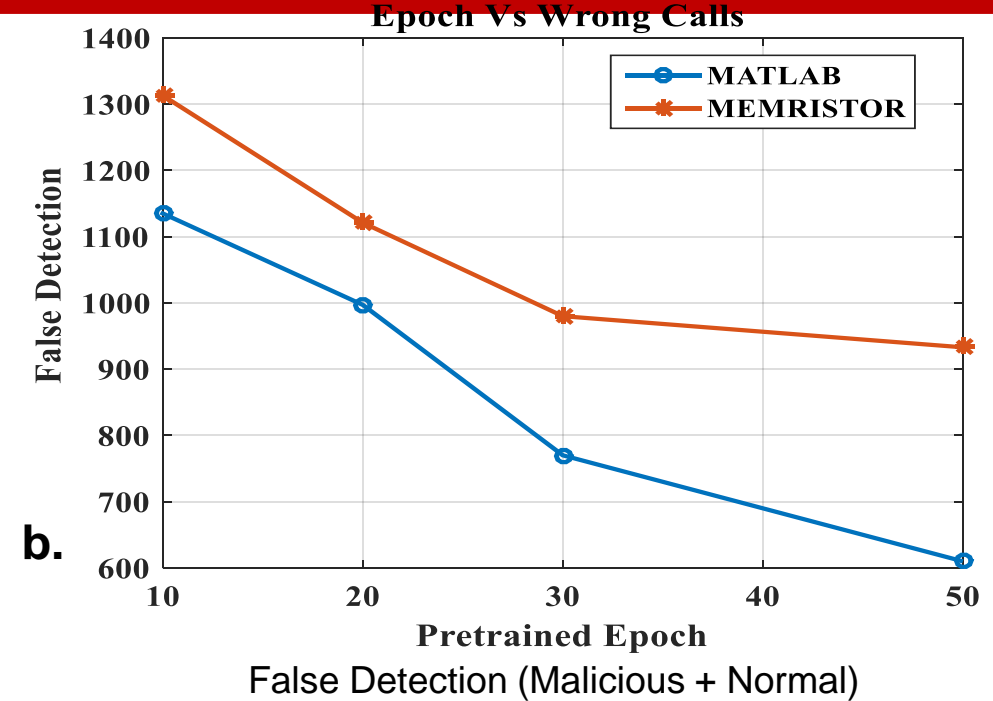
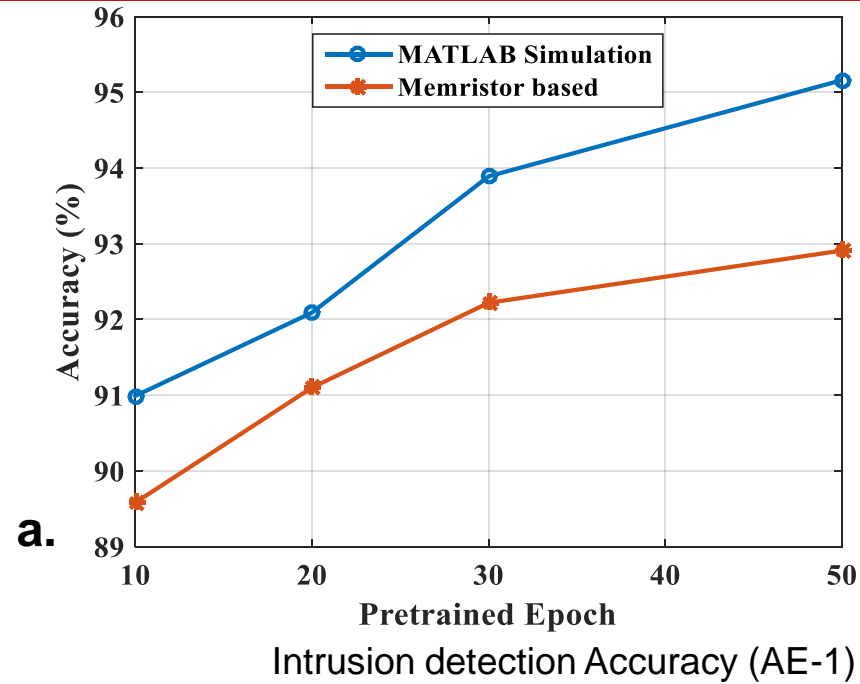


Input feature and regenerated feature of a sample through (AE-1)



Training Error (MSE) in software and memristor X-bar

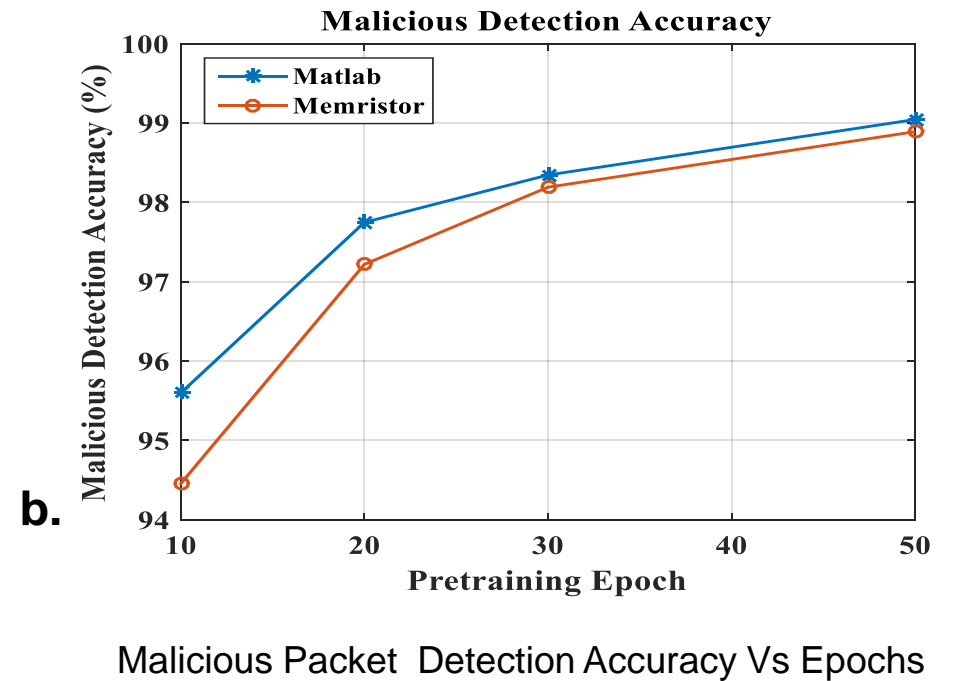
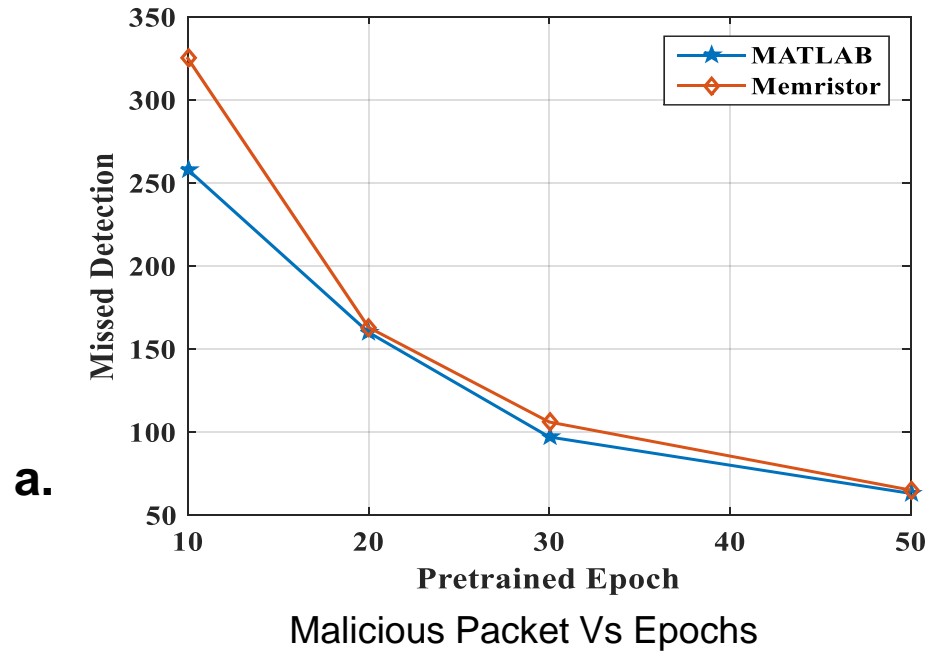
Intrusion Detection Accuracy



$$Accuracy = \frac{N_S - N_F}{N_S} \times 100\%$$

Pretraining Epochs	Global Accuracy	N_{MN}	N_{NM}	N_F	Case
50	95.22%	56	546	602	Software
50	92.91%	65	868	933	Memristor

Intrusion Detection Accuracy (contd.)



Real-time learning and anomaly detection

Real-Time Anomaly Detection:

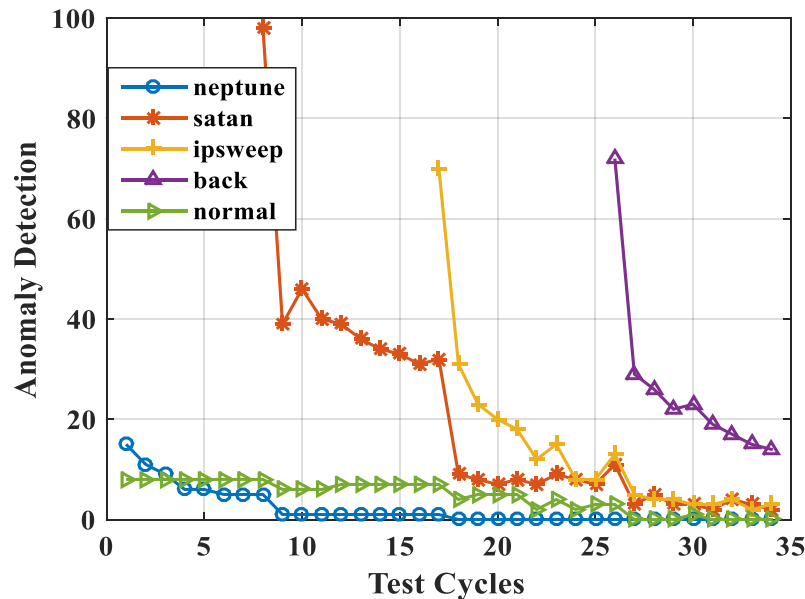
$$T_1 = x_1^1, x_2^1, x_1^2, x_2^2, x_1^3, x_2^3, \dots$$

$$T_2 = x_1^1, x_2^1, x_3^1, x_1^2, x_2^2, x_3^2, \dots$$

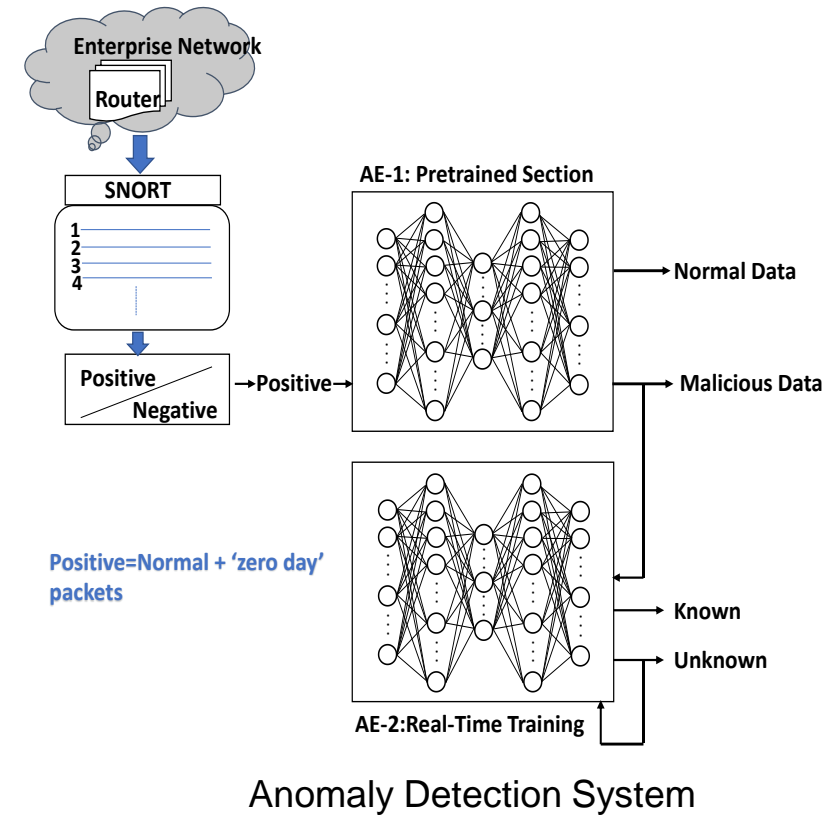
$$T_3 = x_1^1, x_2^1, x_3^1, x_4^1, x_1^2, x_2^2, x_3^2, x_4^2, \dots$$

$$T_4 = x_1^1, x_2^1, x_3^1, x_4^1, x_5^1, x_1^2, x_2^2, x_3^2, x_4^2, x_5^2, \dots$$

$x_1 = normal, x_2 = neptune, x_3 = satan, x_4 = ipsweep, x_5 = back$



Anomaly Detection in real-time



Power, Area and Timing Analysis

- $R_{off} = 1 \times 10^7 \Omega, R_{on} = 5 \times 10^4 \Omega$
- Wire Resistance = $5 \Omega, V_{mem} = 1.3 \text{ volt}$
- Transistor Feature Size : $F = 45 \text{ nm}$
- Op-amp power = $3 \times 10^{-6} \text{ watt}$
- Transistor Size = $50F^2$
- Memristor area = $1 \times 10^4 \text{ nm}^2$

Parameter	Training Data	Recognition Data
Area (mm ²)	0.00271	0.00271
Power (mW)	20.6	7.56
Time (μs)	4.02	0.384
Energy/One Sample (nJ)	82	2.90

Summary

- Introduced the problem and proposed a possible solution
- Presented the Autoencoder with memristor X-bar and the functionalities
- Over all accuracy 92.91% with malicious packet detection accuracy 98.89%
- Presented real-time anomaly detection system
- Explained the power and energy requirement

Current and future work

- Incremental learning algorithm & unseen class detection
- Adaptive learning system for battery power devices



THANK YOU

Questions?