# Kitsune

## AN ENSEMBLE OF AUTOENCODERS FOR ONLINE NETWORK INTRUSION DETECTION

*Yisroel Mirsky, Tomer Doitshman, Yuval Elovici, and Asaf Shabtai*

# Introduction

- **Neural Networks (NN) are great at detecting malicious packets**
  - Great results in literature
    (NNs can learn nonlinear complex patterns and behaviors)
  - But, not so common in practice (*where is my SNORT plugin?*)
- **Existing NN solutions use supervised learning** (e.g., classification):

  1. Collect packets
  2. Label packets: malicious or normal
  3. Train deep NN on labeled data
  4. Deploy the NN model to the device
  5. Execute the model on each packet
  6. When a new attack is discovered, go to #1

# Introduction

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| | |
|---|---|
| *Large storage, many samples of every kind of malicious packet* | 1. Collect packets |
| *Expert with a lof ot time* | 2. Label packets: malicious or nor mal |
| *Large GPU server and time…* | 3. Train deep NN on labeled data |
| | 4. Deploy the NN model to the device |
| *Handle thousands of packets a second (e.g., a simple router)* | 5. Execute the model on each packet |
| | 6. When a new attack is discovered, go to #1 |

# **Kitsune** Overview

*A **Kitsune**, in Japanese folklore, is a mythical fox-like creature that has a number of tails, can mimic different forms, and whose strength increases with experience.*

*So too, **Kitsune** has an ensemble of small neural networks (autoencoders), which are trained to mimic (reconstruct) network traffic patterns, and whose performance incrementally improves overtime.*

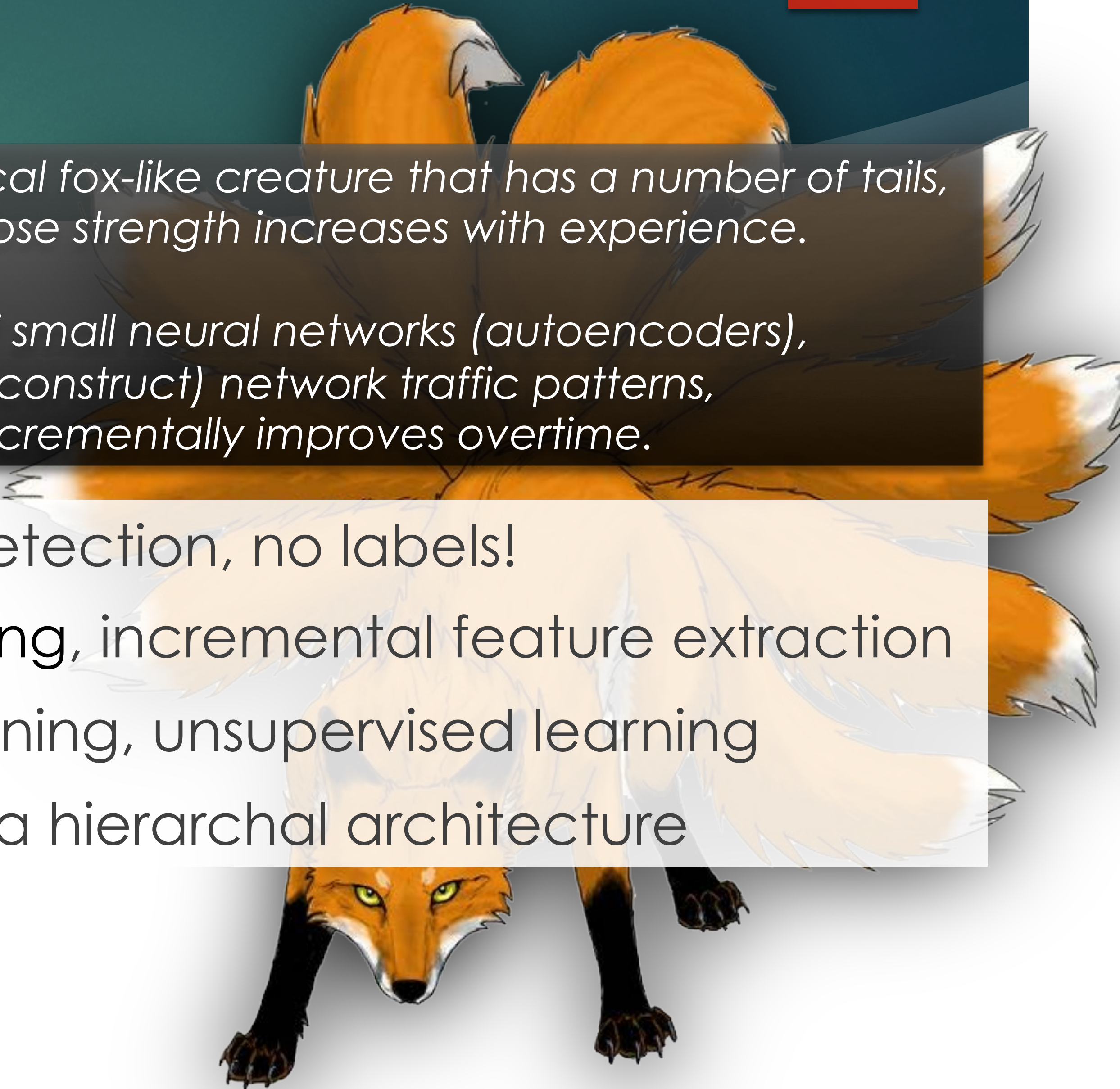
Enables NN on network traffic

- **Unsupervised:** Anomaly detection, no labels!
- **Online**: Incremental learning, incremental feature extraction

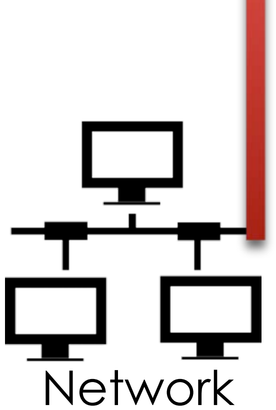
Enables realistic deployments

e.g., routers

- **Plug-and-Play**: On-site training, unsupervised learning
- **Light-weight**: The NN uses a hierarchal architecture



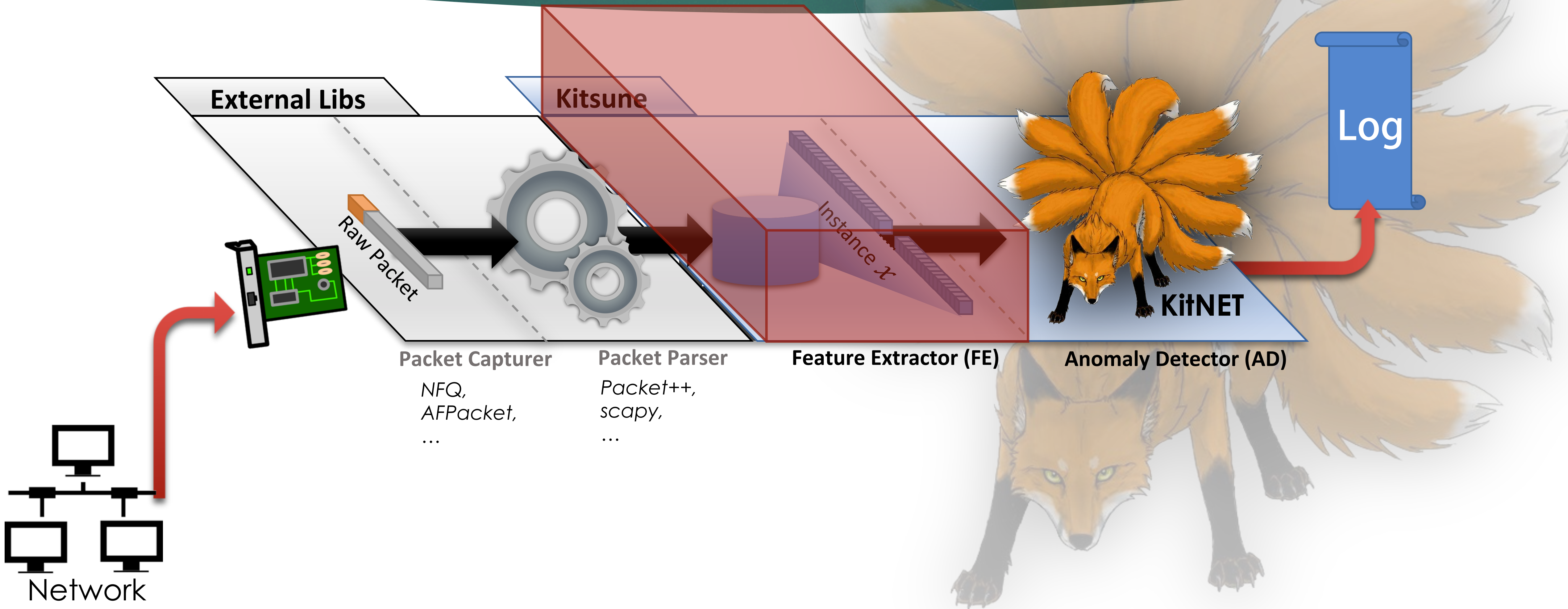
# **Kitsune** Framework


**NIDS are Located on:**

- Gateways/Routers
- Servers
- Dedicated Devices
  *(e.g., PI attached to a mirror port)*

# **Kitsune** Framework



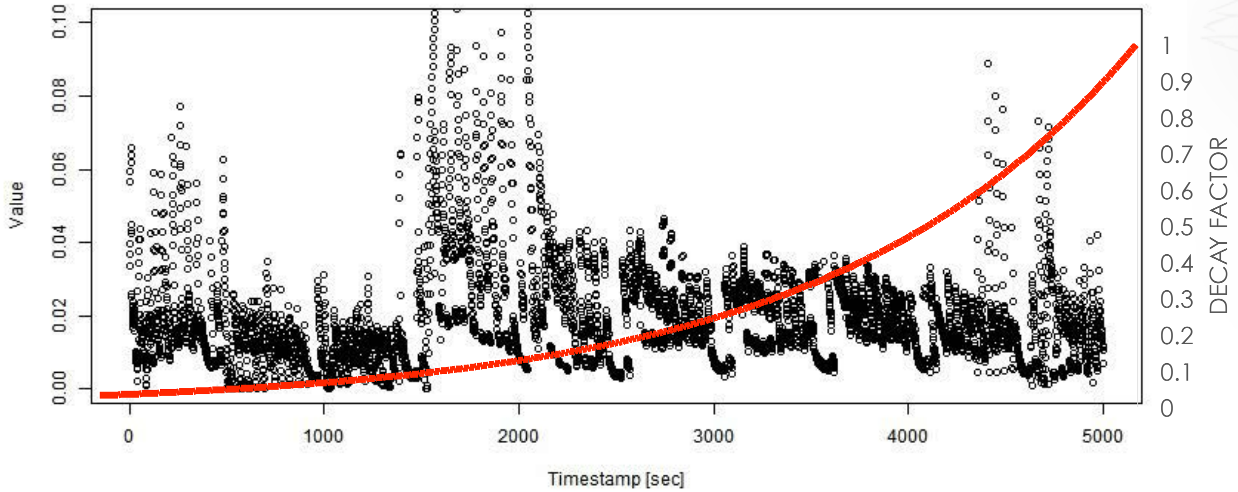
# **Kitsune** Feature Extractor (FE)

- FE uses **damped incremental statistics** to *efficiently* measure *recent* traffic patterns

**Decay Factor:**

$d_\lambda(t) = 2^{-\lambda t}$

**An unbounded stream of values** $S=\{x1, x2, \dots\}$




**Objective:** Compute the stats ($\mu,\sigma,\dots$) over the recent history of $S$, given limited memory and non-uniform sample rates (timestamps)

Incremental Statistic Object:

$$IS := (w, LS, SS, SR, t_{last})$$

Basic Stats:

$$\mu = \frac{LS}{w}, \sigma = \sqrt{\left|\frac{SS}{w} - \left(\frac{LS}{w}\right)^2\right|}, \dots$$

Update IS with $\mathbf{x_i}$:

$$\gamma \leftarrow d_\lambda(t_{cur} - t_{last})$$

$$IS \leftarrow (\gamma w + 1, \gamma LS + x_i, \gamma SS + x_i^2, \gamma SR + r_i r_j, t_{cur})$$

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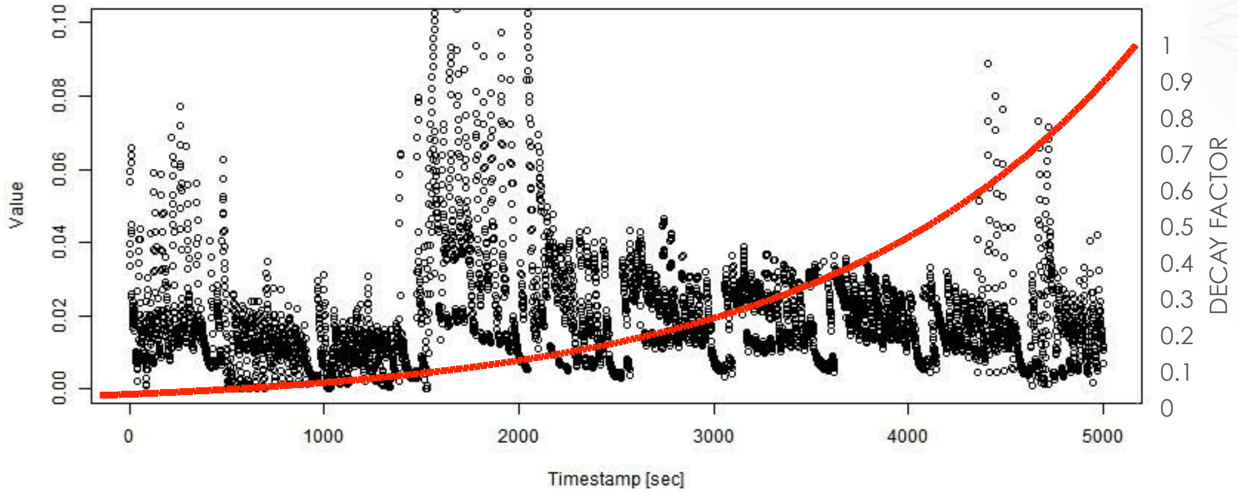


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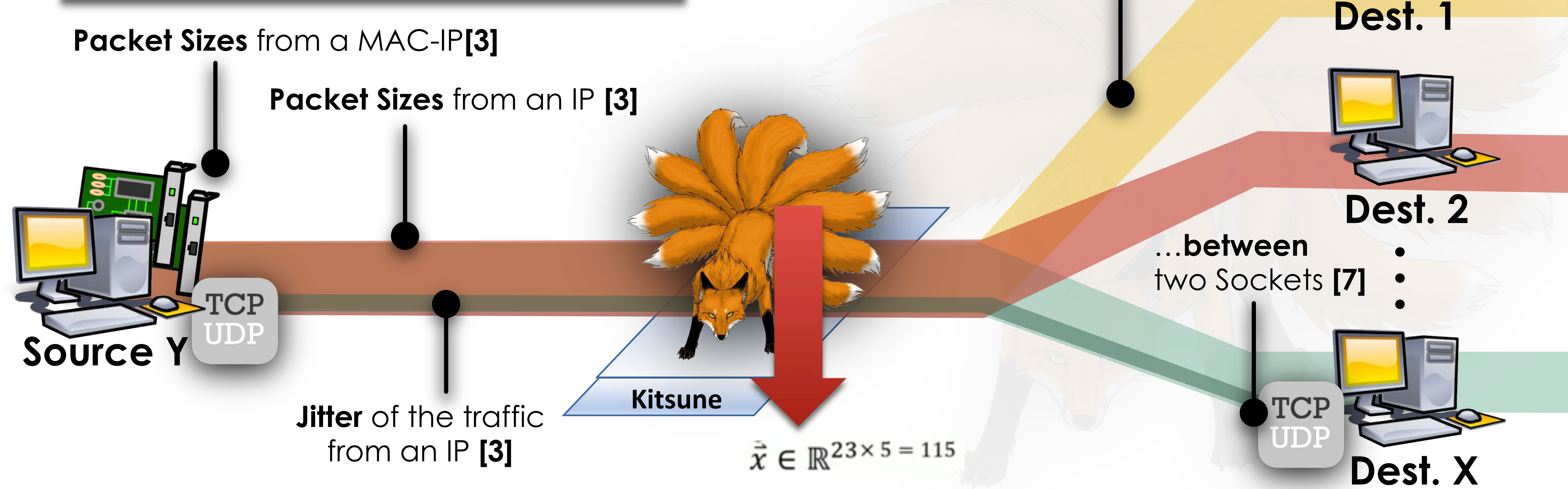
| Type | Statistic | Notation | Calculation |
|---|---|---|---|
| 1D | Weight | $w$ | $w$ |
| | Mean | $\mu_{S_i}$ | $LS/w$ |
| | Std. | $\sigma_{S_i}$ | $\sqrt{\lvert SS/w - (LS/w)^2 \rvert}$ |
| 2D | Magnitude | $\lVert S_i, S_j \rVert$ | $\sqrt{\mu_{S_i}^2 + \mu_{S_j}^2}$ |
| | Radius | $R_{S_i,S_j}$ | $\sqrt{\left(\sigma_{S_i}^2\right)^2 + \left(\sigma_{S_j}^2\right)^2}$ |
| | Approx. Covariance | $Cov_{S_i,S_j}$ | $\frac{SR_{ij}}{w_i + w_j}$ |
| | Correlation Coefficient | $P_{S_i,S_j}$ | $\frac{Cov_{S_i,S_j}}{\sigma_{S_i}\sigma_{S_j}}$ |

# **Kitsune** Feature Extractor (FE)

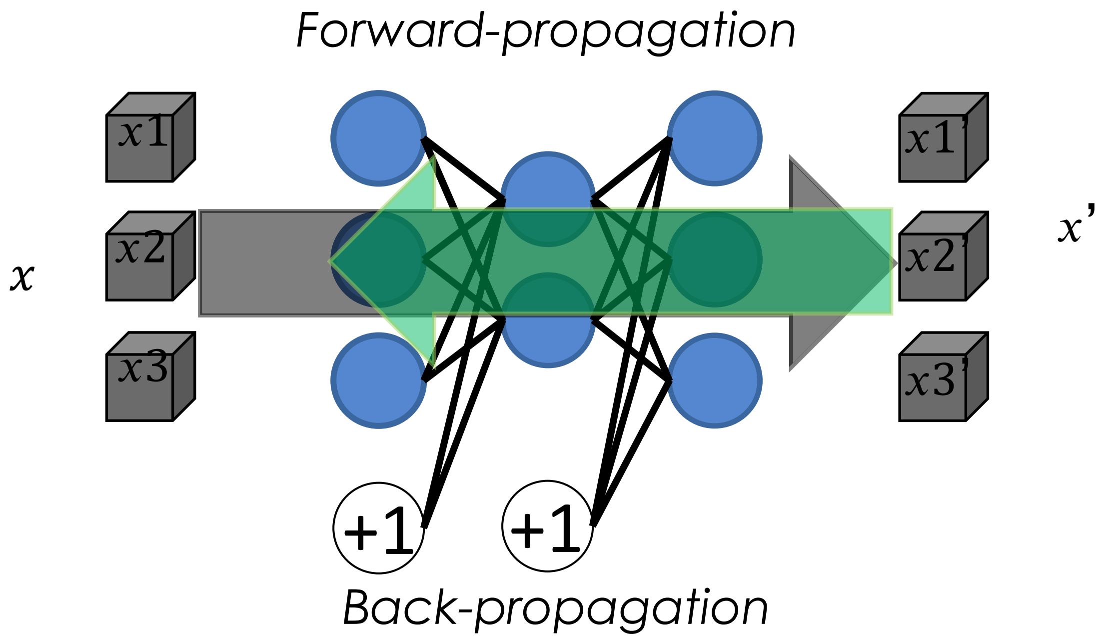
*Potentially thousands of streams … each with 5 inc-stats of 100ms, 500ms, 1.5sec, 10sec, and 1min*



# The **KitNET** Anomaly Detector

## Anomaly Detection with an Autoencoder

- **An Autoencoder is a NN which is trained to reproduce its input after compression**
- **There are two phases:** Train Execute




Error: $x - x'$

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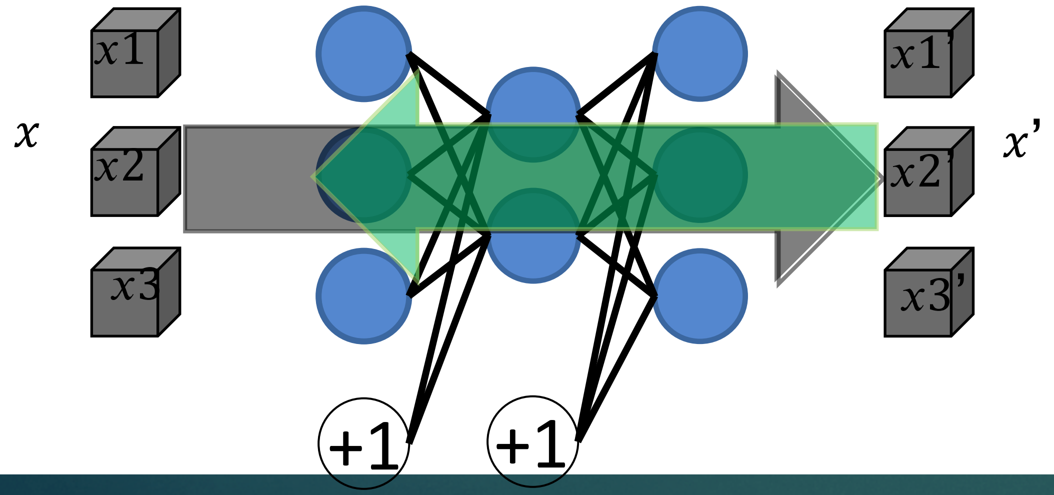


*Back-propagation*

### Reconstruction Error

$$\mathrm{RMSE}\left(\vec{x},\vec{y}\right)=\sqrt{\frac{\sum_{i=1}^{n}\left(x_i-y_i\right)^2}{n}}$$

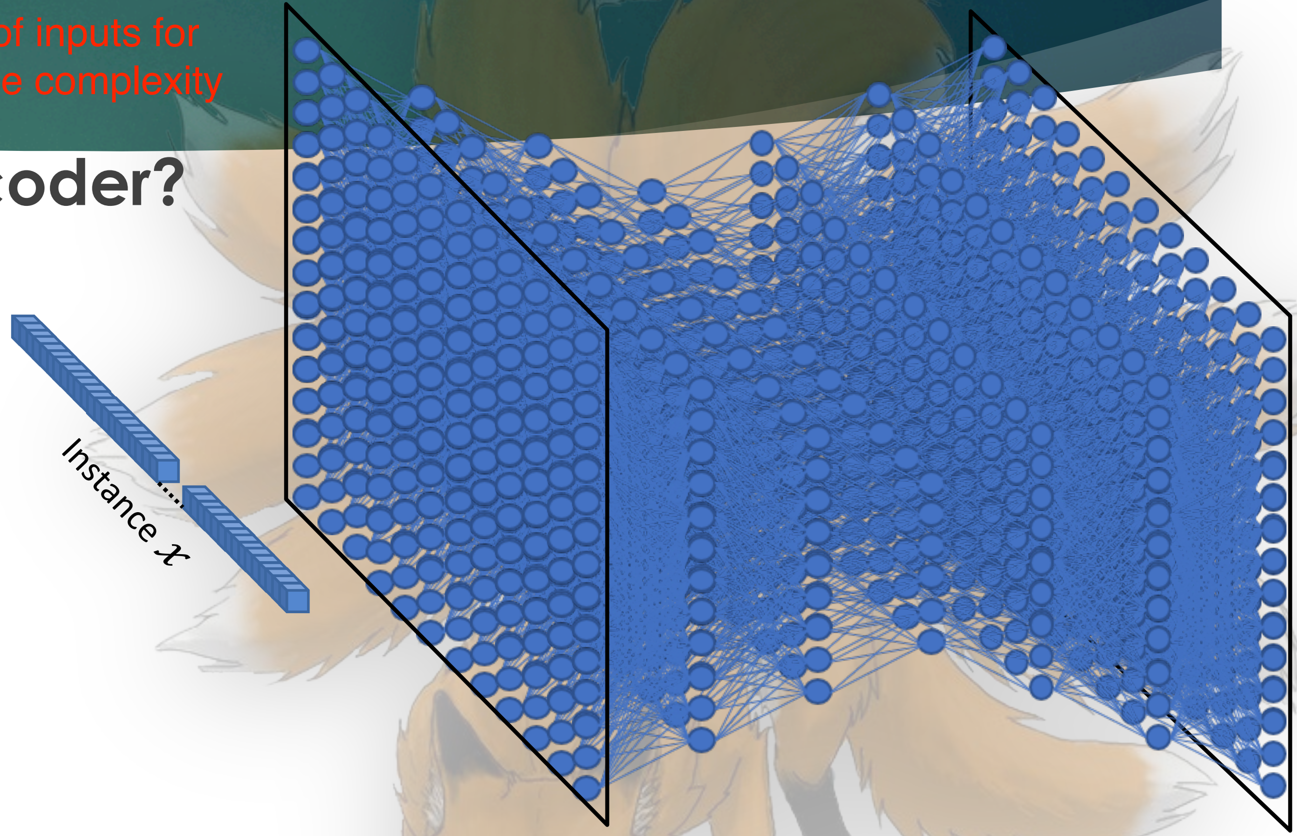
**Low value**: $x$ is normal
**High value**: $x$ is abnormal
*(does not fit known concepts)*

# The **KitNET** Anomaly Detector

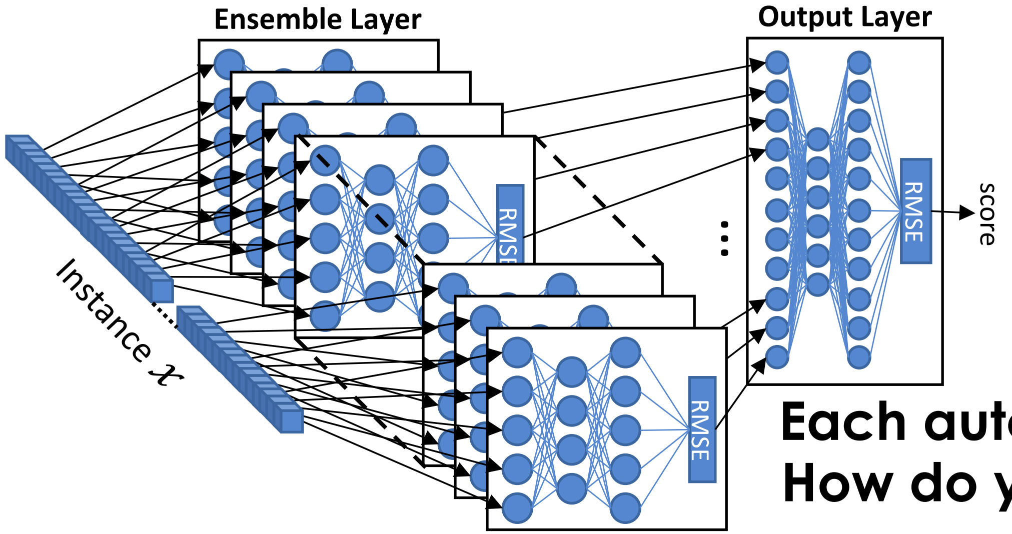
KitNET has one main input parameter, m: the maximum number of inputs for each autoencoder in KitNET's ensemble. This parameter affects the complexity of the ensemble in KitNET.

## Why not one massive deep autoencoder?

- Curse of dimensionality!
- Train/Execute Complexity




## Our Solution:

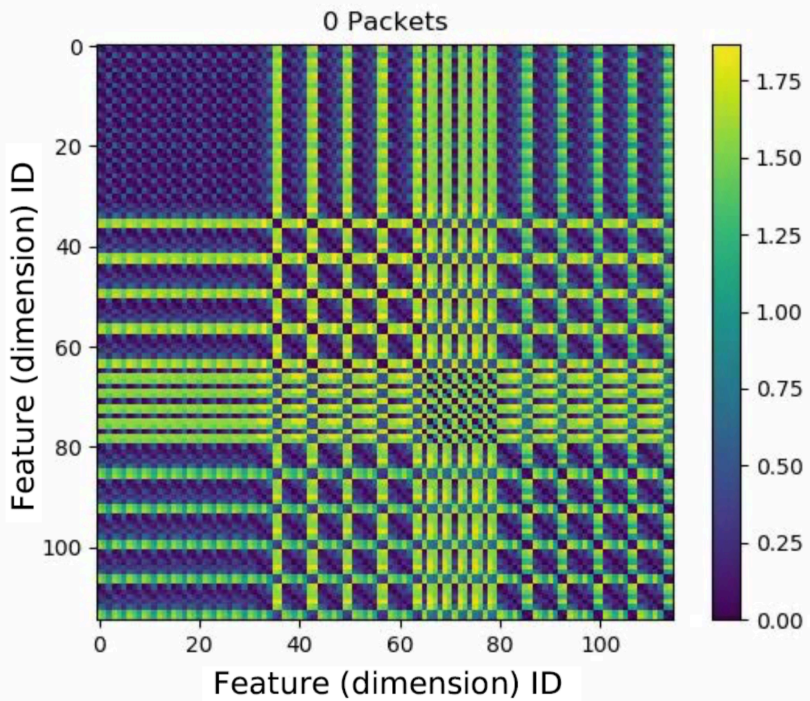



**Each autoencoder receives a group of correlated features**
**How do you find the groupings online?**

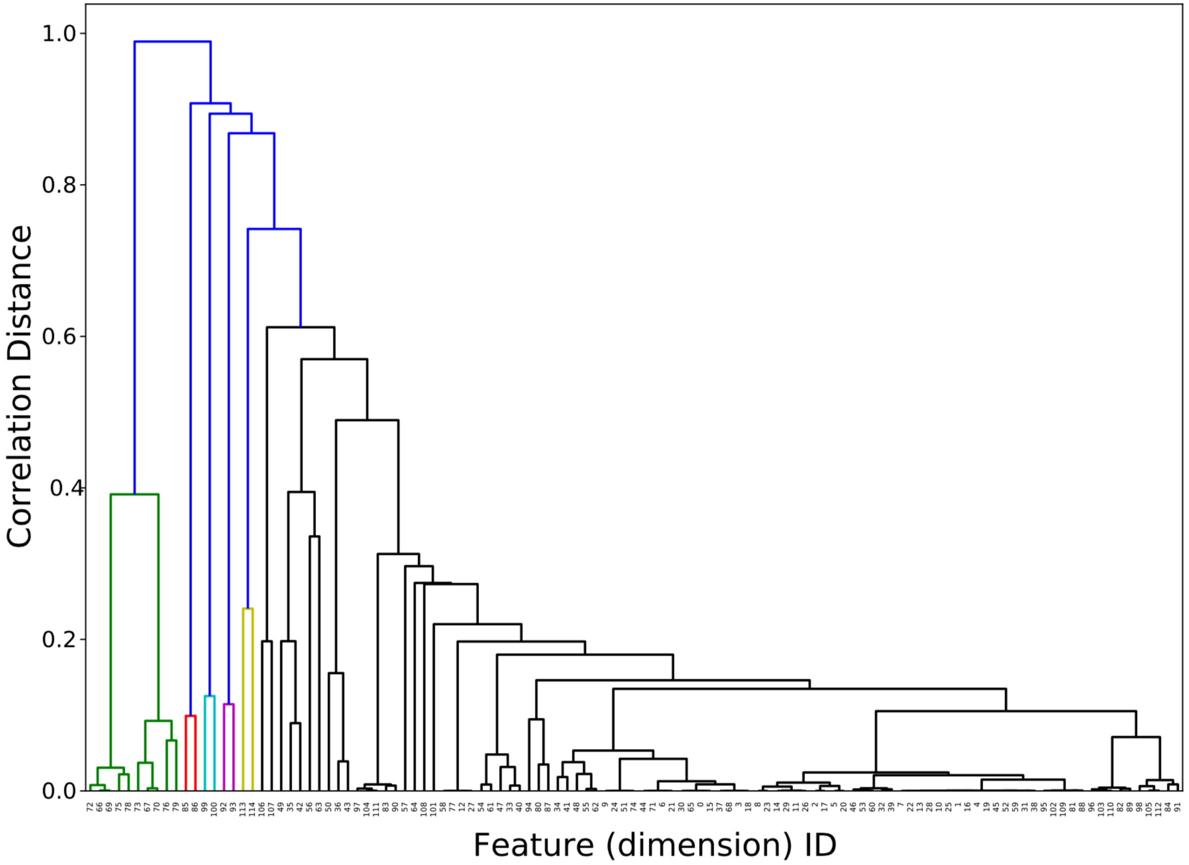
# The **KitNET** Anomaly Detector

- For the first N observations ($x$), incrementally update a correlation distance matrix

$$D = [D_{ij}] = 1 - \frac{(x_i - \bar{x}_i) \cdot (x_j - \bar{x}_j)}{\|(x_i - \bar{x}_i)\|_2 \|(x_j - \bar{x}_j)\|_2}$$




- Perform **one-time** agglomerative hierarchal clustering on $D$ (fast)



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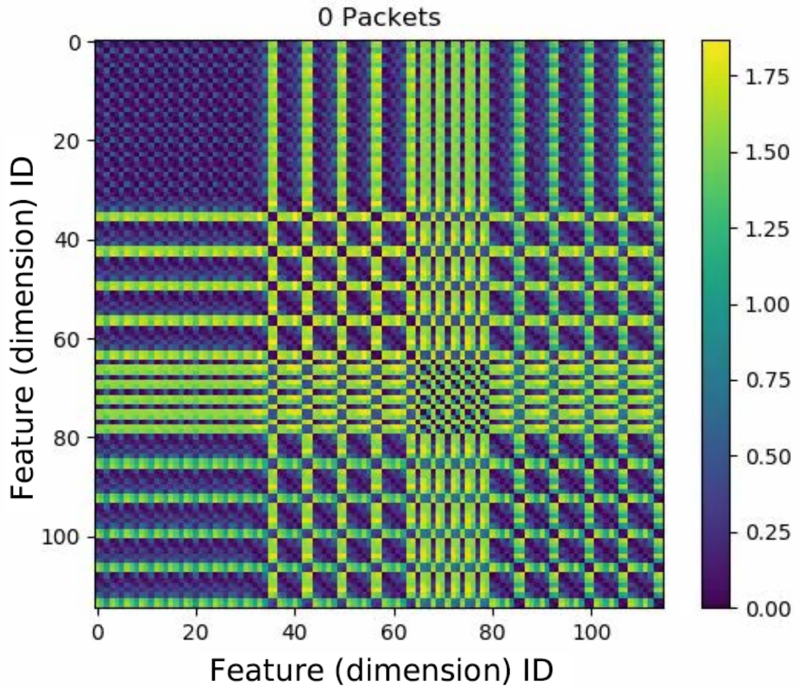


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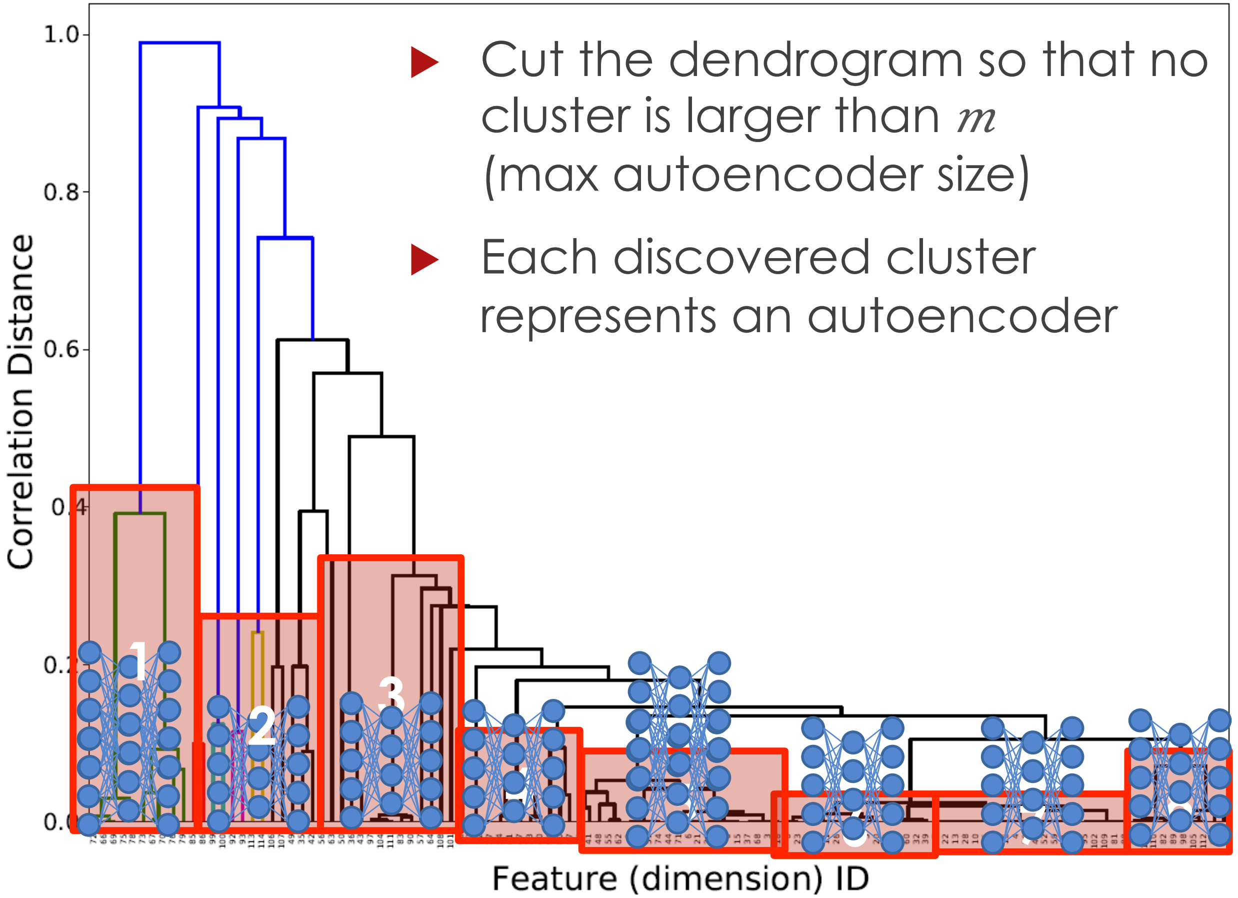
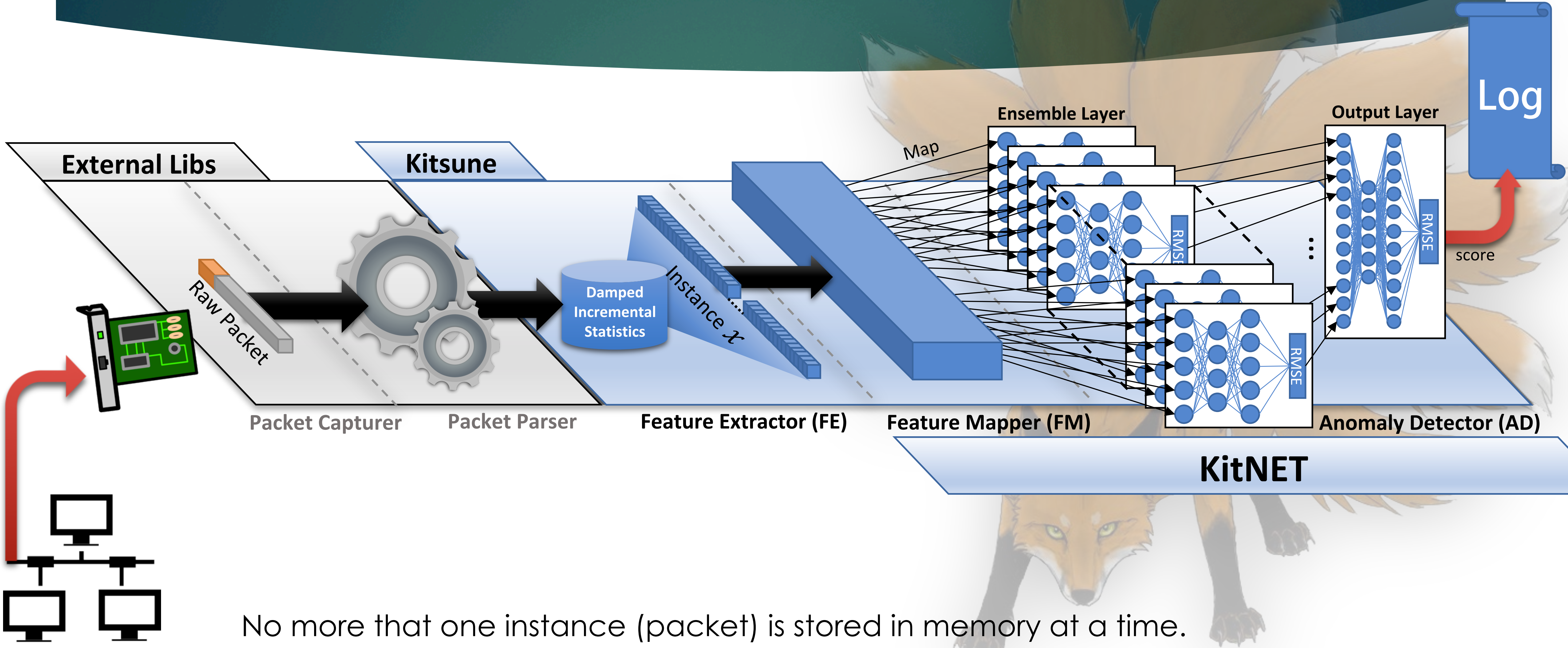



- Cut the dendrogram so that no cluster is larger than $m$ (max autoencoder size)
- Each discovered cluster represents an autoencoder

# Kitsune NIDS

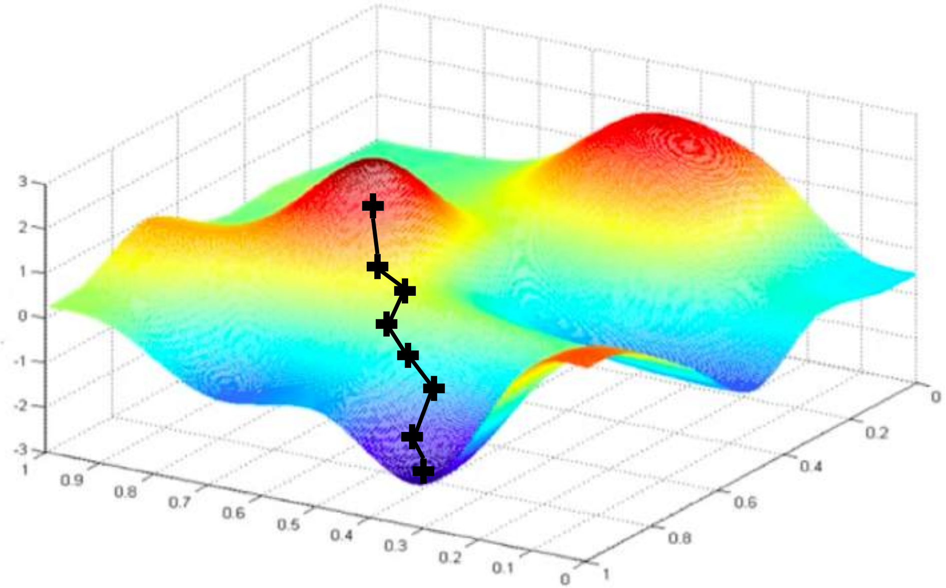



No more that one instance (packet) is stored in memory at a time.

# Gradient Descent

**Algorithm**

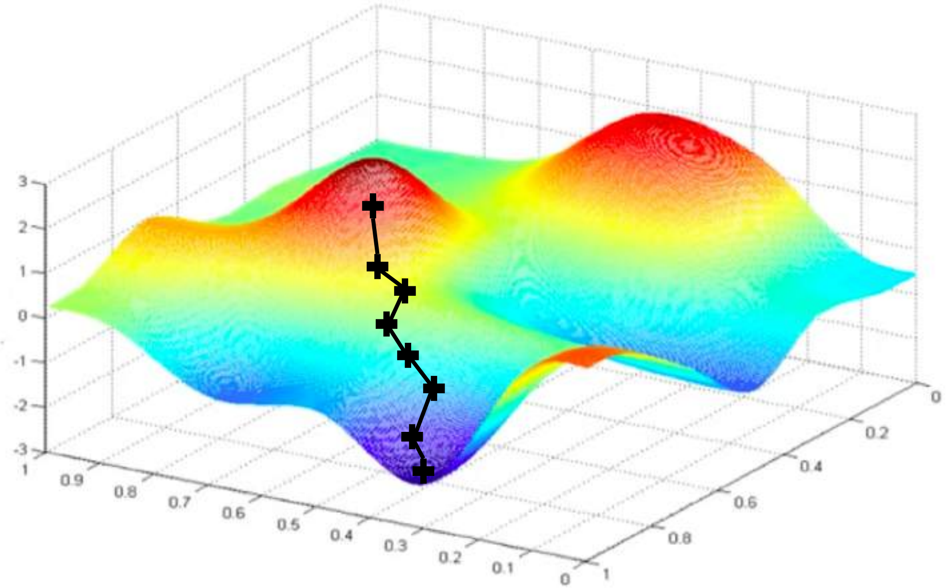
1. Initialize weights randomly $\sim\mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
4. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Return weights



# Stochastic Gradient Descent

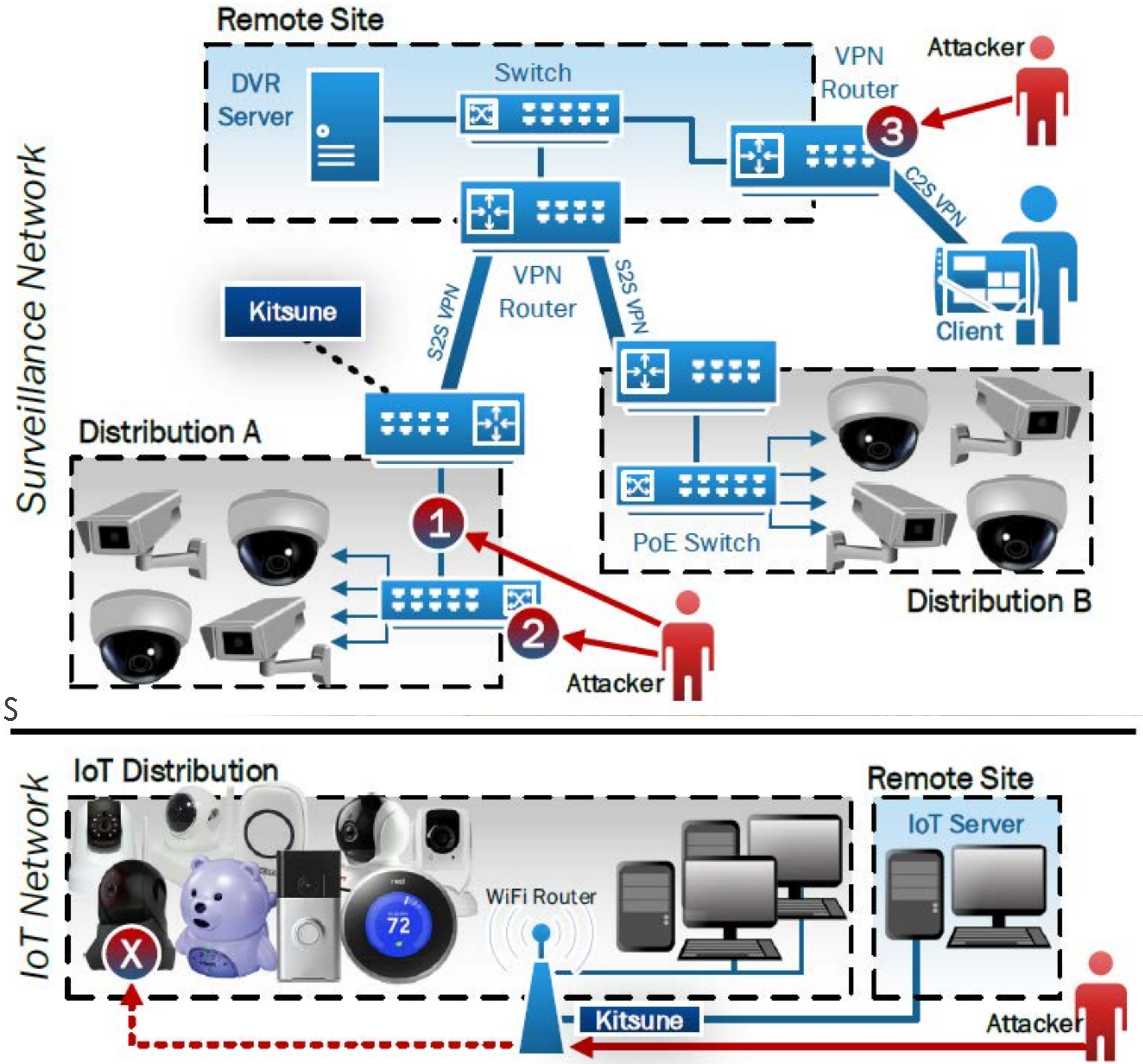
**Algorithm**

1. Initialize weights randomly $\sim\mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Pick single data point $\boldsymbol{i}$
4. Compute gradient, $\frac{\partial J_i(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
6. Return weights



# Experimental Results

- **Networks**:
  - Surveillance
  - IoT
- **Algorithms**:
  - **Signature-based**: Suricata with over 13,465 emerging threat rules
  - **Anomaly-based**:
    - **Batch**: GMM, Isolation Forest
    - **Online**: pcStream & iGMM



# Experimental Results

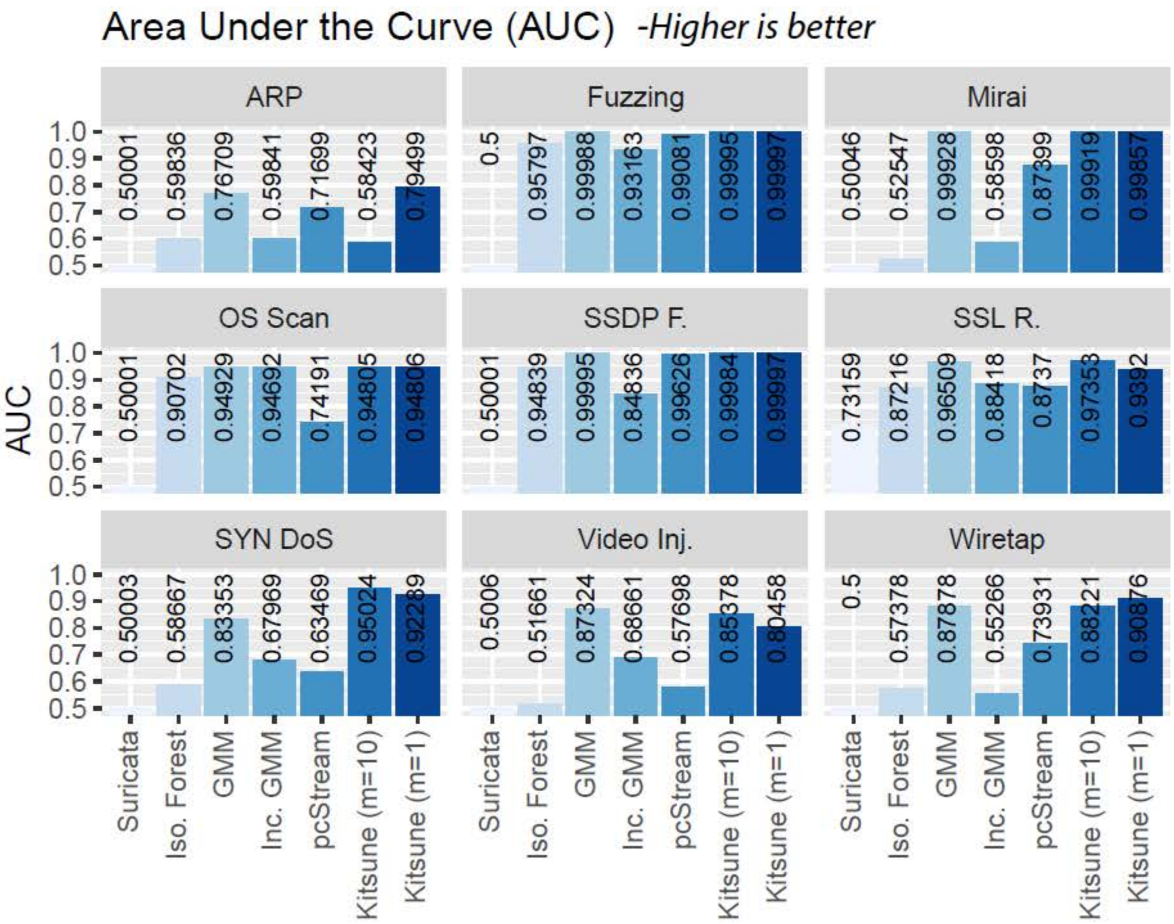


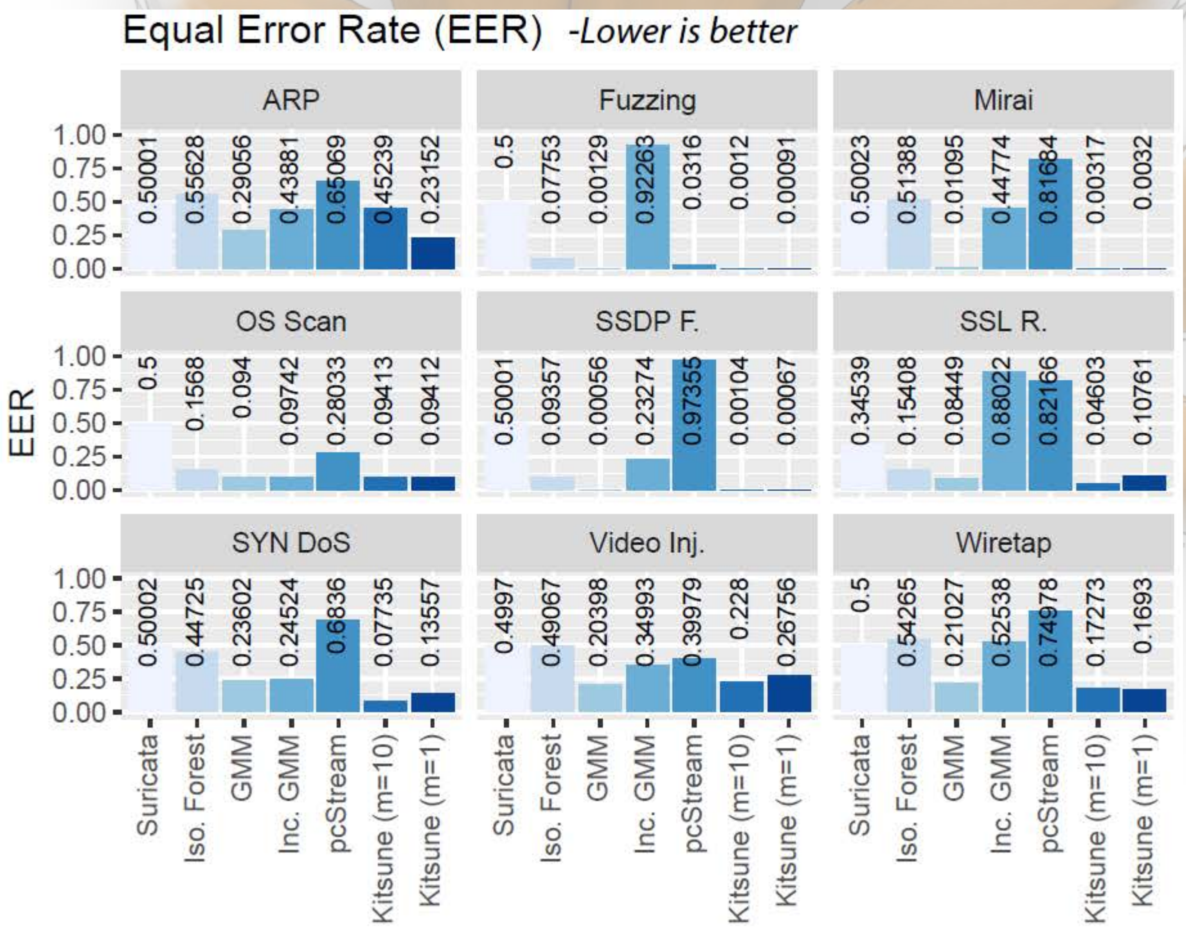
## Attacks

| Attack Type | Attack Name | Tool | **Description:** *The attacker…* | Violation | Vector | # Packets | Train [min.] | Execute [min.] |
|---|---|---|---|---|---|---|---|---|
| *Recon.* | **OS Scan** | Nmap | *…scans the network for hosts, and their operating systems, to reveal possible vulnerabilities.* | **C** | 1 | 1,697,851 | 33.3 | 18.9 |
| | **Fuzzing** | SFuzz | *…searches for vulnerabilities in the camera's web servers by sending random commands to their cgis.* | **C** | 3 | 2,244,139 | 33.3 | 52.2 |
| *Man in the Middle* | **Video Injection** | Video Jack | *…injects a recorded video clip into a live video stream.* | **C, I** | 1 | 2,472,401 | 14.2 | 19.2 |
| | **ARP MitM** | Ettercap | *…intercepts all LAN traffic via an ARP poisoning attack.* | **C** | 1 | 2,504,267 | 8.05 | 20.1 |
| | **Active Wiretap** | Raspberry PI 3B | *…intercepts all LAN traffic via active wiretap (network bridge) covertly installed on an exposed cable.* | **C** | 2 | 4,554,925 | 20.8 | 74.8 |
| *Denial of Service* | **SSDP Flood** | Saddam | *…overloads the DVR by causing cameras to spam the server with UPnP advertisements.* | **A** | 1 | 4,077,266 | 14.4 | 26.4 |
| | **SYN DoS** | Hping3 | *…disables a camera's video stream by overloading its web server.* | **A** | 1 | 2,771,276 | 18.7 | 34.1 |
| | **SSL Renegotiation** | THC | *…disables a camera's video stream by sending many SSL renegotiation packets to the camera.* | **A** | 1 | 6,084,492 | 10.7 | 54.9 |
| *Botnet Malware* | **Mirai** | Telnet | *…infects IoT with the Mirai malware by exploiting default credentials, and then scans for new vulnerable victims network.* | **C, I** | X | 764,137 | 52.0 | 66.9 |

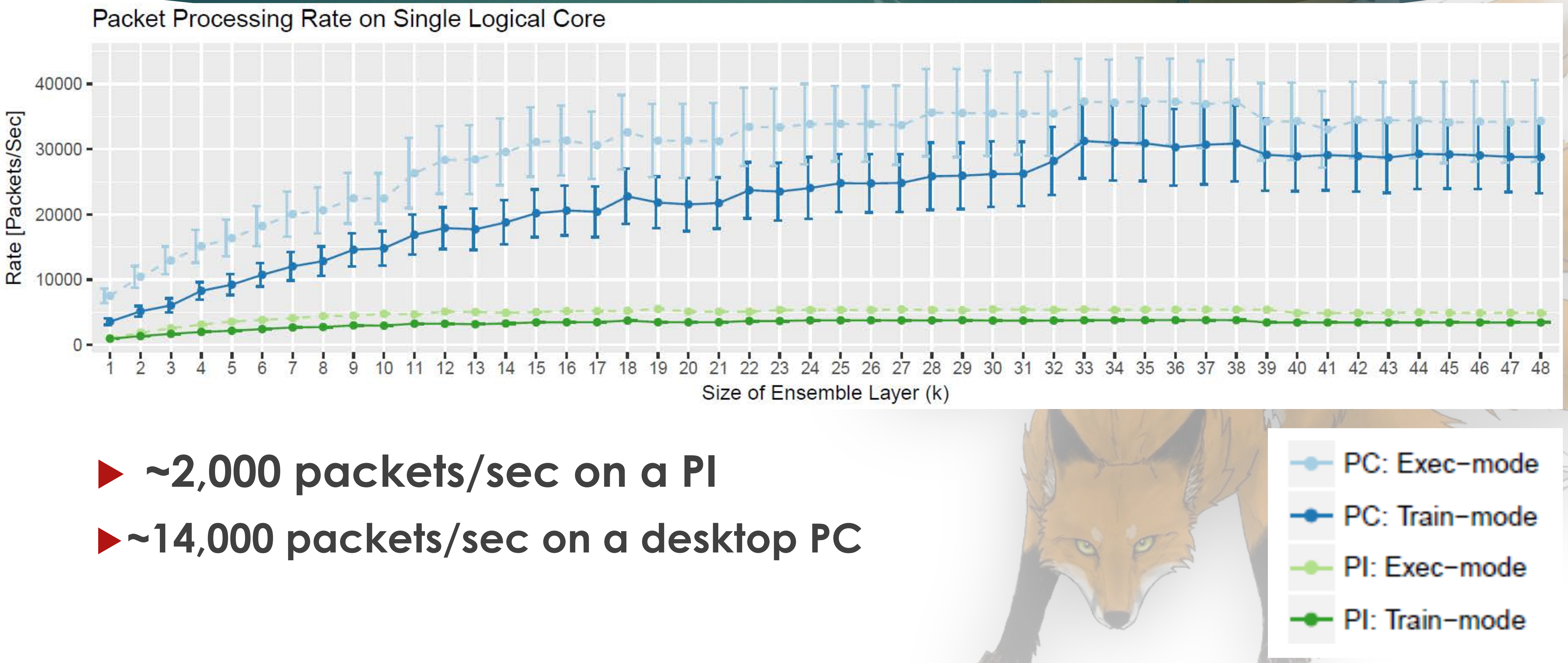
# Experimental Results

Kitsune has one main parameter, m ∈ {1, 2, . . . , n}, which is the maximum number of inputs for any one autoencoder of KitNET's ensemble



# Experimental Results



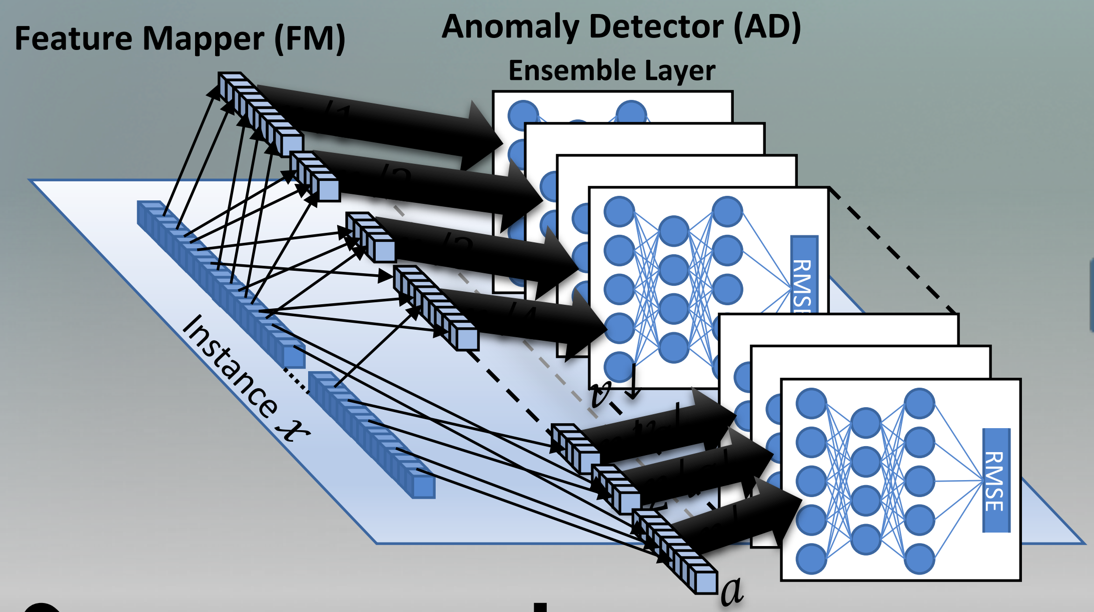

- ~2,000 packets/sec on a PI
- ~14,000 packets/sec on a desktop PC

# Summary

- In the past, NNs on NIDS were used for the task of **classification**
- We propose using NNs for the task of **anomaly detection**
  - Eliminates the need for labeling data (endless traffic & unknown threats)
  - Enables plug-and-play
- **Kitsune Achieves this by,**
  - Efficient feature extraction
  - Efficient anomaly detection (**KitNET**)

# KitNET

The core-anomaly detection algorithm of Kitsune




python

**Source code:**

https://github.com/ymirsky/KitNET- py

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Thank you!