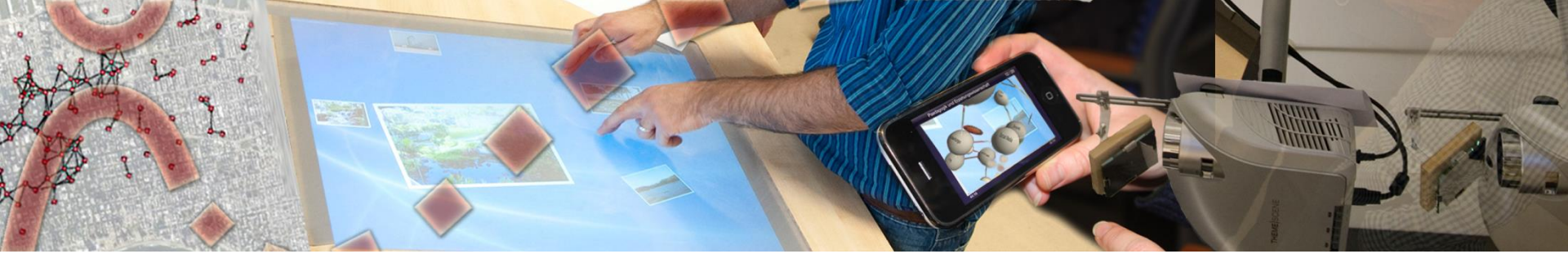

Analyzing Flow-based Anomaly Intrusion Detection using Replicator Neural Networks

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The Beautiful World of IoT

The Beautiful World of IoT

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Goals

- Performance
- Usability
- Transparency
- Accessibility
- Ubiquity
- **Security?????**

The Beautiful World of IoT?

- **Latest IoT news:**
  - **09-2014:** IoT – Major players agree on goals, but little else
  - **12-2014:** New Hacker-Friendly search engine that lists vulnerable IoT devices (censys.io)
  - **11-2015:** Millions of IoT Devices using the same hard-coded crytpo-keys
  - **09-2016:** World's largest 1Tbps DDoS Attack launched from 152,000 hacked smart devices
  - **10-2016:** Largest botnets consists of mostly IoT devices
  - **10-2016:** 12-Year-Old SSH bug exposes more than 2 million IoT devices
  - **Recently:** Mirai botnet, WannaCry, etc

Outline

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~~1. Motivation~~

2. Introduction

- What is all this about?

3. Background

- Intrusion Detection is Large Networks

4. Intrusion Detection using Replicator Neural Networks

- Detecting Anomalies in Network Flows
- Replicator Neural Networks

5. Evaluation

- Experiments and Results

6. Conclusion and Future Work

Introduction:
What is all this about?

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- **Understanding the Title:**
  - Analyzing Flow-based Anomaly Intrusion Detection using replicator Neural Networks

- **Analyzing Flow-based**
  - **Purpose:** analyze network data encoded as flows
  - **Enables:** affordable analysis of massive traffic

- **Anomaly Intrusion Detection**
  - **Purpose:** automatically detect deviations from normality
  - **Enables:** identification of new attacks without user intervention

- **using Replicator Neural Networks**
  - **Purpose: classify**
  - **Enables:** unsupervised (and robust) identification of anomalous traffic

Background:
Intrusion Detection in Large Networks

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- Large networks are the new battle ground
  - Botnets
  - Coordinated Crowds
  - Denial of Service attacks
  - … and all other coordinated attacks
- Network attacks affect the victim and the Internet infrastructure
  - Disruption to the targets and the service providers
  - Defensive mechanisms need to be **further from the edge**
- Large Networks are difficult to monitor
  - Thousands of heterogeneous devices
  - Terabytes of data (every hour)
  - Attacks are easily overlooked

Background:
Intrusion Detection in Large Networks

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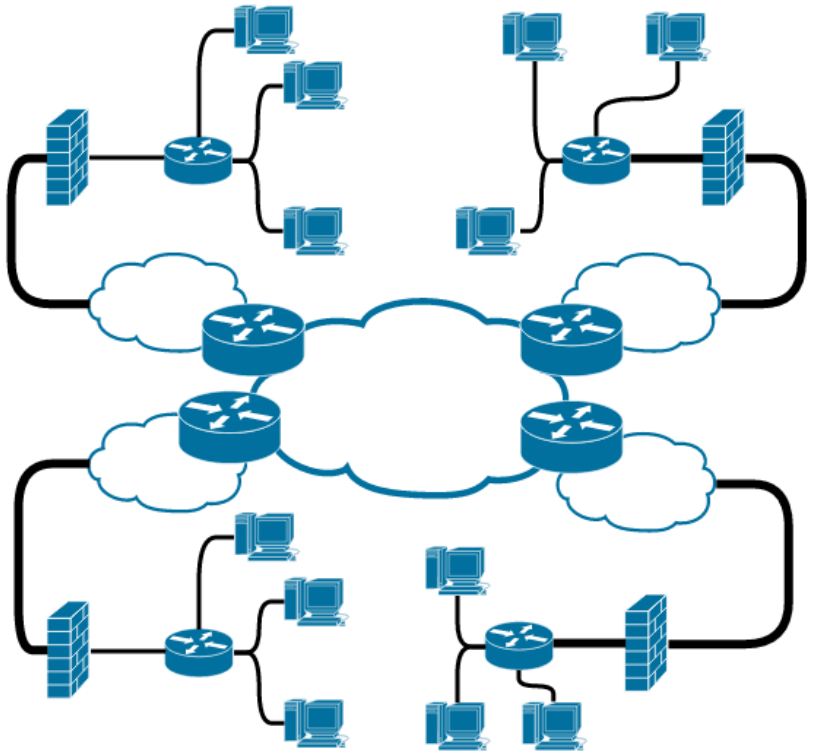
- Detecting anomalies in large networks



- ML Requirements
  1. Scalable detection
  2. High accuracy (with low false positives)
  3. Work without supervision (unsupervised)
  4. Resilience to model poisoning

Background:
Intrusion Detection in Large Networks

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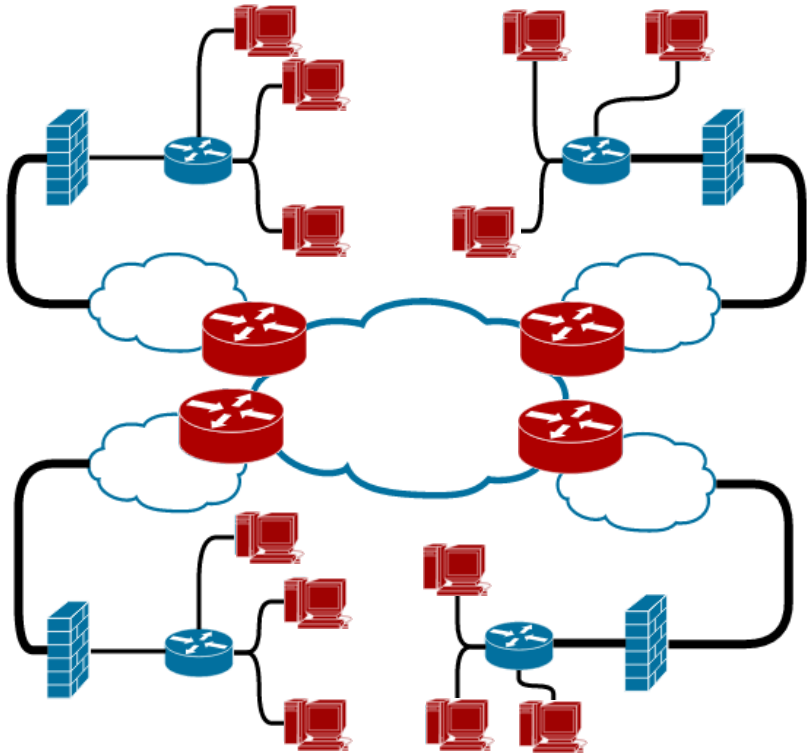
- Detecting anomalies in large networks



- Data Requirements
  1. Detect away from the edge
     - Detecting at the edge

     - Detecting away from the edge

  2. Reduce dimensionality of network data

Flows

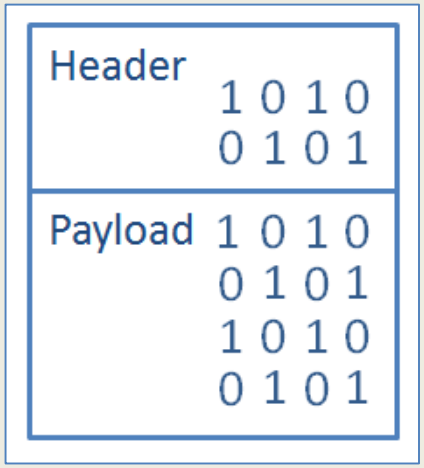
Intrusion Detection in Large Networks

- Working with network data: Network Flows

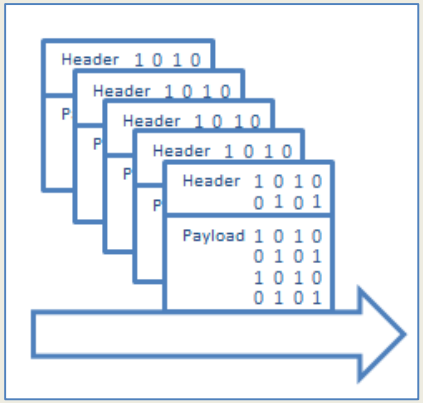
Bytes

1 0 1 0 1 0 1 0
0 1 0 1 0 1 0 1
1 0 1 0 1 0 1 0
0 1 0 1 0 1 0 1

Packets



Flows



Background:
Intrusion Detection in Large Networks

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- Network Flows

#	Time	Src IP	Dst IP	Src Port	Dst Port	Bytes	Packets
1	X	21.65.71.124	110.45.78.12	51478	80	512	245
2	X	64.73.26.110	21.65.71.124	49652	80	56	1523
3	Y	110.45.78.12	64.73.26.110	58471	21	10,548	235
4	Y	21.65.71.124	110.45.78.12	49652	23	45,687	672
...							

- Condense representation of network data
- Communication summary of two endpoints

Detecting Anomalies in Network Flows

- Extracting features from network flows

#	Time	Src IP	Dst IP	Src Port	Dst Port	Bytes	Packets
1	X	21.65.71.124	110.45.78.12	51478	80	512	245
2	X	64.73.26.110	21.65.71.124	49652	80	56	1523
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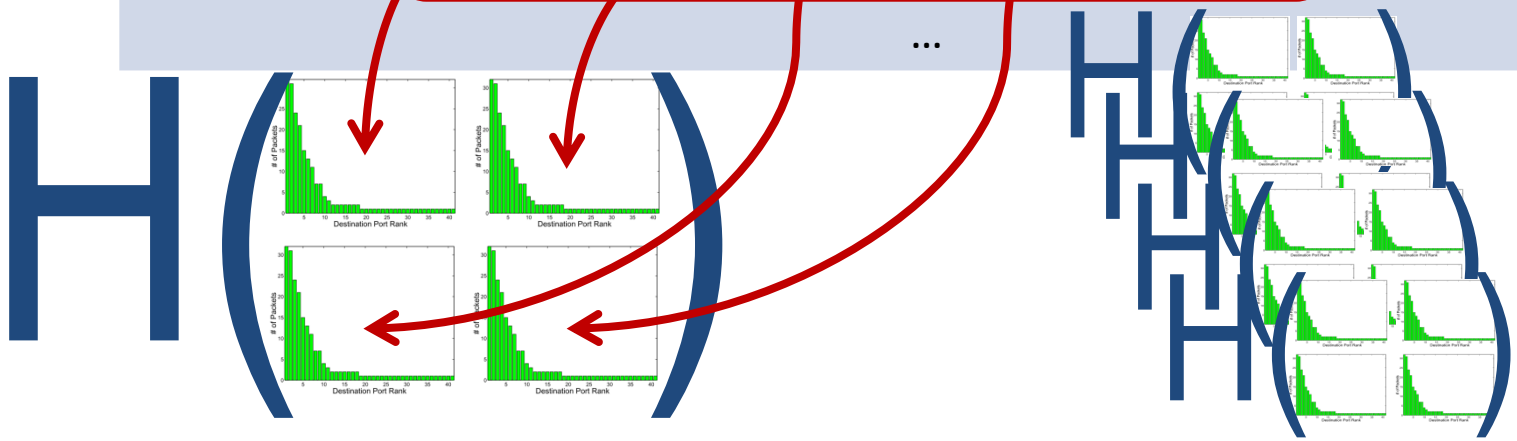


$$H^i = \{h_1^i, h_2^i, \dots, h_D^i\}$$

$$X = \{H^1, H^2, \dots, H^N\}$$

Detecting Anomalies in Network Flows

$$H^i = \{h_1^i, h_2^i, \dots, h_D^i\} \qquad X = \{H^1, H^2, \dots, H^N\}$$

- Anomaly Detection using the **Subspace Method**
  - Principal Component Analysis (PCA) on the X set
  - Compute all Principal Components
  - Select components that define the:
    - Normal subspace – Components capturing the most variance of X
    - Abnormal subspace – Components not used for the normal subspace

	PC1	PC2	PC3	PC4
Eigenvalue	1.0563	0.2062	0.0511	0.0213
Variance	79.11%	15.44%	03.83%	01.60%
Accumulated Variance	79.11%	94.56%	98.39%	100%

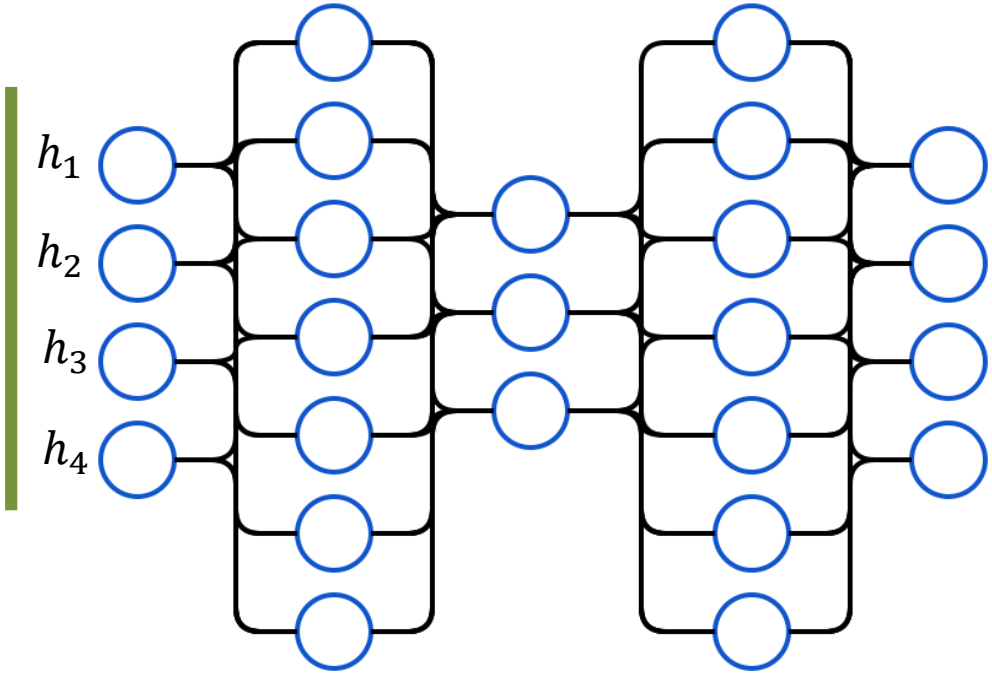
  - Disadvantages
    - PCA is inefficient with many dimensions
    - Abnormal space prone to contamination

Replicator Neural Networks

$$H^i = \{h_1^i, h_2^i, \dots, h_D^i\}$$

$$X = \{H^1, H^2, \dots, H^N\}$$

- Replicator Neural Networks



- Same number of inputs and outputs
- Middle layer smaller than input
- Between 3 to 5 layers
- Original purpose:
  - data compression
  - dimensionality reduction

Anomaly Score:

$$AS(x) = \frac{1}{D}\sum_{i=1}^{D}(\varepsilon_i)^2$$

Evaluation
Experiments and Results

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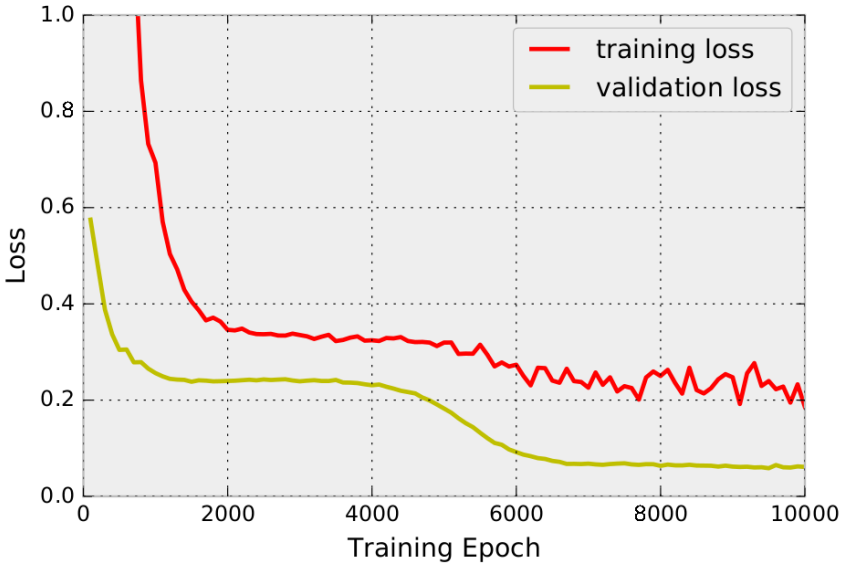
- 4 different sets of experiments
  1. Learning representations of network flows
  2. Detecting anomalies in the training data
  3. Detecting injected attacks
  4. ~~Comparison against the Subspace Method (PCA)~~

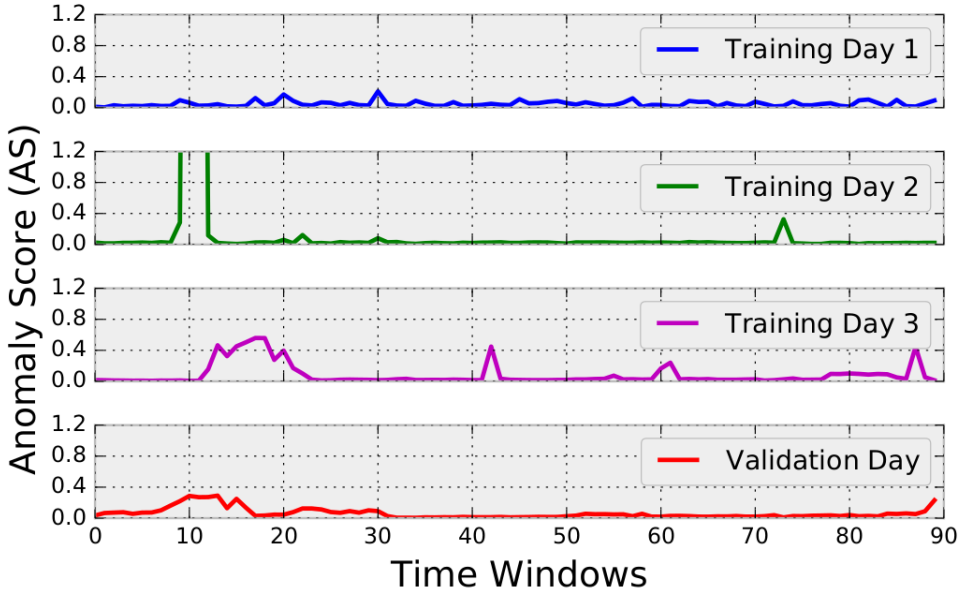
- Experimental setup
  - Dataset: MAWI lab
    - 3 training days
    - 1 validation day
  - Network flows exported every 10 seconds

Experiments and Results

1. Learning representations of network flows

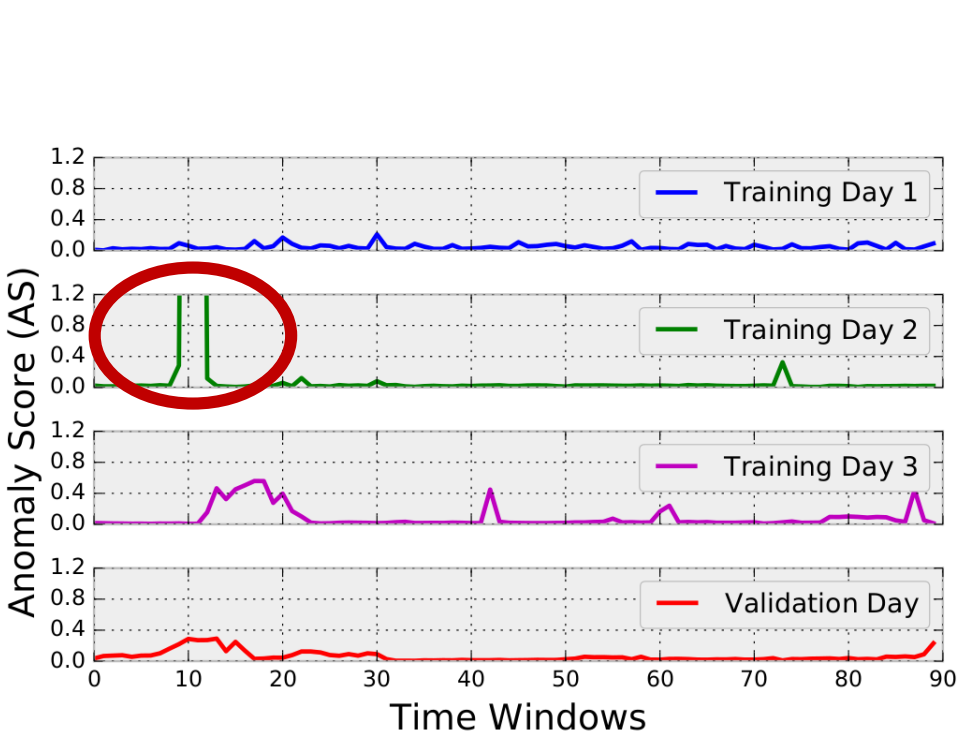
- Standard Replicator Neural Network with 5 layers
- 50% dropout in layers 2 and 4

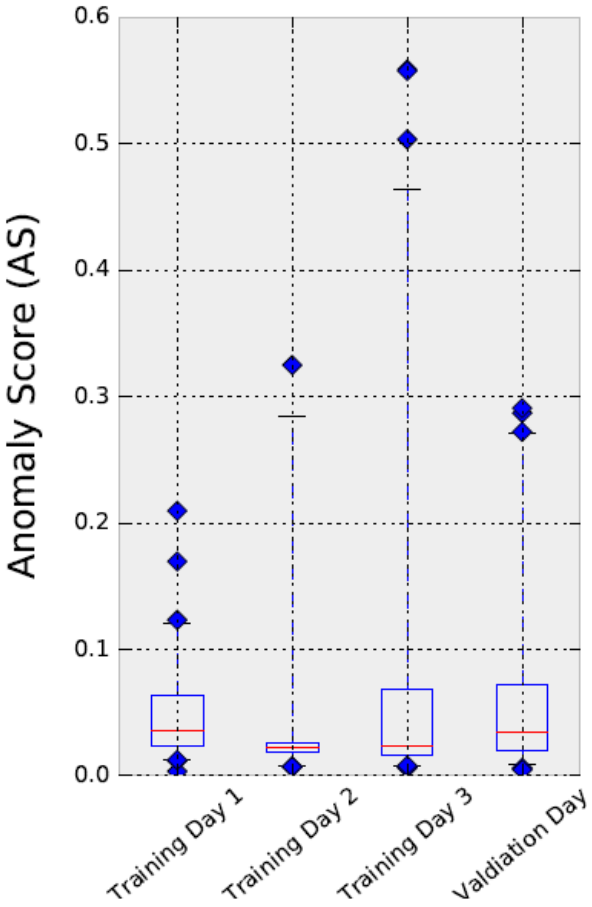




Experiments and Results

2. Detecting anomalies in the training data

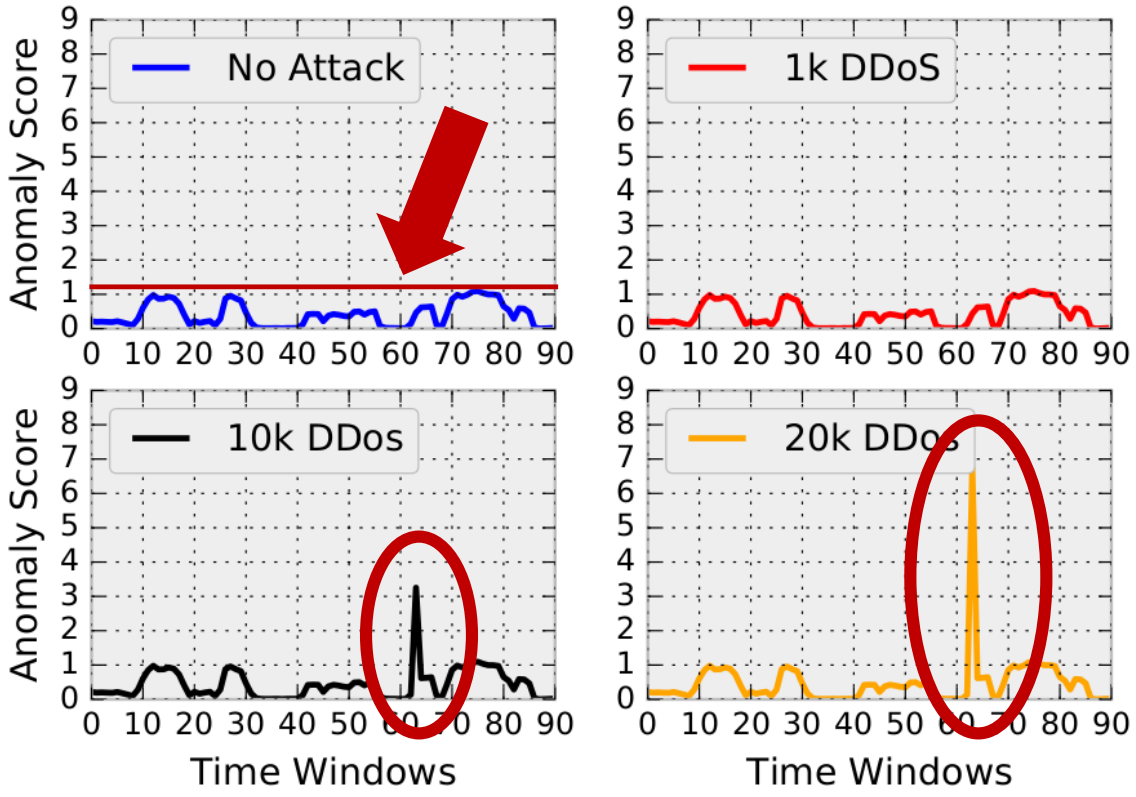




Experiments and Results

3. Detecting injected attacks

- DDoS attack with 4 intensities



Conclusion and Future Work

- Replicator Neural Networks (RNNs)
  - Effectively detect resource exhaustion attacks and network profiling techniques
  - Work in large and real-world backbone internet data
  - Detect attacks in the training data as well as new (unseen) data
  - No labeled data needed

- Future Work
  - Test different autoencoder configurations (beyond RNNs)
  - Add Gaussian noise to the inputs and other input transformation techniques
  - Use network flows and meta-flow features
  - Test other relevant deep learning techniques