Anomaly Detection in Cyber Networks using Graph-node Role-dynamics and NetFlow Bayesian Normalcy Modeling

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Agenda

• Introduction
• Advanced Persistent Threats
• Graph-node Role-dynamics
• Bayesian Normalcy Modeling
• Summary
Introduction

- **Context Aware INference for Advanced Persistent Threat (CAIN for APT)**
  - DARPA Phase II SBIR

- **Challenge**
  - Stealthy cyber attacks slip past state-of-the-art defenses, dealing crippling blows to critical US military and civilian infrastructure

- **Goal**
  - Rapid, automated, and accurate prioritization of cyber alerts provides timely and comprehensive cyber situational awareness (SA)

- **Technical Approach**
  - Novel graph-analytics makes sense of noisy IDS sensors
  - Novel Bayesian Dynamic Flow Model flags odd network traffic
  - Tests and evaluations with APT simulations
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Advanced Persistent Threats

- Often associated with nation-state espionage
- Targets include private organizations & nation-states
- Low and Slow: Attack campaigns may last months
- Notoriously difficult to detect


Image: https://www.secureworks.com/blog/advanced-persistent-threats-apt-a
Simulated APT Scenarios

- **Simulation attributes**
  - Approx. 1 month of data per scenario
  - Servers, laptops, switches
  - Linux & Windows machines
  - Normal & attacked behavior
  - Generates IDS alerts and NetFlow traffic
  - Detailed attack timeline

- **Hurricane Panda simulation**
  - Attack distributed over 3 days
  - Database injection to gain credentials
  - Lateral movement and firewall deactivation

- **Energetic Bear (Crouching Yeti) simulation**
  - Attack distributed over 3 hours
  - Email phishing to redirect user to malicious website
  - Lateral movement through network using a remote-desktop exploit
  - Attacker attempted to clean-up logs and other traces
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Graph-based Approach

- Fuses disparate IDSs
- Captures alert interdependencies
- Efficiently represents many alerts
- Robust to circumvention
- Unsupervised
- Facilitates causal analysis
- Optimal parameters determined automatically
Making Sense of Noisy IDS Sensors with Graph Analytics

- Novel, graph-based analysis of IDS alerts
  - Load IDS alerts into alert graph
  - Detect graph anomalies

- Advantages of graph-based approach:
  - Captures alert interdependencies
  - Fuses disparate IDSs
  - Efficiently represents alerts
  - Robust to circumvention

Alert Graphs from Hurricane Panda Simulation

Akoglu et al. 2014
Alert Graphs

- Graph of alerts (Not network topology)

**OSSEC Alert (Host IDS)**

```
** Alert 1480536972.16316356: syslog, vsftpd, connection_attempt 2016 Nov 30 20:16:12 (host)
10.10.255.79 -> /var/log/vsftpd.log Rule: 11401
(level 3) -> 'FTP session opened.' Src IP:
10.10.255.77 Wed Nov 30 15:17:25 2016 [pid 14562]
```

**Snort Alert (Network IDS)**

```
[**] [Potentially Bad Traffic] [Priority: 2] {TCP}
10.10.255.77:38989 -> 10.10.255.50:5432
```
Alert Graphs

- Graph of alerts (Not network topology)
- Alert properties become nodes
- Node colors indicate property type

OSSEC Alert (Host IDS)


Snort Alert (Network IDS)

Alert Graphs

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Alert Graph

- Graph of alerts (Not network topology)
- Alert properties become nodes
- Node colors indicate property type
- Edges connect nodes that co-occur in alerts
- Edges weighted by frequency of co-occurrence
Alert Graphs

- Cyber attacks change IDS alert logs
- Intuition
  - Changes in alert logs modify alert graph
  - Anomalies in the graph features (properties) may indicate cyber attacks
- Quick test
  - Degree of IP nodes shows marked changes during simulated attack
  - But a single feature is likely insufficient
  - What features should we track?
  - Should we model all features for anomalies?
Role Dynamics

- Infeasible to model every feature of every node
- Instead, use graph-based anomaly detection algorithms
- Role dynamics (Rossi et al., 2012)
  - Collect features and factorize as roles
  - Roles provide a succinct, integrated summary across a large number of features
  - Output is probability of membership in each role, for each node
  - Application to IDS alerts is novel
Role Dynamics

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  - Application to IDS alerts is novel
  - Track role memberships over time
Role Dynamics

• Why role dynamics?
  – Linear
  – Weighted
  – Dynamic
  – Attributed
  – Unsupervised
  – Explainable
  – Extensible
  – Automated parameter selection
  – Available

• Explainable
  – Identifies anomalous nodes
  – Helps with causal analysis

• Automated parameter selection
  – Recursive features
  – Optimal number of roles
  – Set during a training period
Finding Role Anomalies

• Role anomalies
  – Now we have roles over time for all nodes in graph
  – How to identify anomalies in the roles?

• Aggregate changes into a few useful metrics
  – For example, average magnitude of the rate of change in role membership:
    \[ \sum_{n=1}^{N} |P_n(t) - P_n(t-1)| / N \]
  – Monitor metrics for anomalies

APT Attack Start
Results: APT Scenario 1

- **Hurricane Panda scenario**
  - Virtual network of servers, laptops, switches, etc.
  - Linux & Windows machines
  - 9 Nov 2016 – 3 Dec 2016
  - Attack distributed 30 Nov – 2 Dec
  - Snort (NIDS) & OSSEC (HIDS)
  - Database injection to gain credentials
  - Lateral movement and firewall deactivation

- **Results**
  - Using threshold at 0.3, CAIN identified 4 anomalies
  - Second two anomalies relate to machines coming online for the first time
  - Last anomaly corresponds with the start of Hurricane Panda’s attack
Results: APT Scenario 2

- **Energetic Bear scenario**
  - Same network as Hurricane Panda
  - 1 Jan 2017 – 4 Feb 2016
  - Attack on Jan 31, 2017
  - 644,067 OSSEC (HIDS) alerts
  - Email phishing to redirect user to malicious website
  - Lateral movement through network using a remote-desktop exploit
  - Attacker attempted to clean-up logs and other traces

- **Results**
  - Using threshold at 0.3, CAIN identified 2 anomalies
  - Third anomaly corresponds with the start of the Energetic Bear attack
Conclusions: Making Sense of Noisy IDS Sensors with Graph Analytics

• **Graph-based Role-dynamics:**
  – Fuses IDS sensor alerts
  – Reduces >750k alerts to a handful of anomalies
  – Identifies anomalies in IDS alerts during APT attacks

• **Success in 2 APT scenarios demonstrates:**
  – Robust to different types of APTs and attack vectors
  –Insensitive to IDS systems
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Bayesian Dynamic Flow Model

- Unsupervised model of NetFlow traffic dynamics
- Assume data follows Poisson distribution
  \[ x_t \sim \text{Poisson}(\phi_t) \]
- Model temporal evolution as Gamma-Beta discount model
  - Prior: \[ x_t \sim P(\phi_t | x_{0:(t-1)}) = \Gamma(\delta_t r_{t-1}, \delta_t c_{t-1}) \]
  - Posterior: \[ x_t \sim P(\phi_t | x_{0:t}) = \Gamma(\delta_t r_t, \delta_t c_t) \]

(X. Chen, et al. 2016)
Results
Bayesian Dynamic Flow Model

Identifies anomaly during APT attack

- Complementary to graph-based role-dynamics
- Multiple methods corroborate detection
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• Developed two complementary anomaly detection techniques
  • IDS: Graph-based Role Dynamics
  • NetFlow: Bayesian Dynamic Flow Model

• Tested on two APT scenarios
  • Hurricane Panda
  • Energetic Bear (a.k.a. Crouching Yeti)

• Successful anomaly detection in two APT scenarios suggests:
  – Robust to different types of APTs and attack vectors
  – Insensitive to IDS systems
References

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