

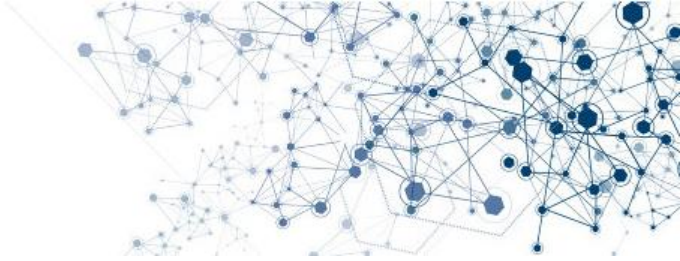


# Anomaly Detection in Cyber Networks using Graph-node Role-dynamics and NetFlow Bayesian Normalcy Modeling

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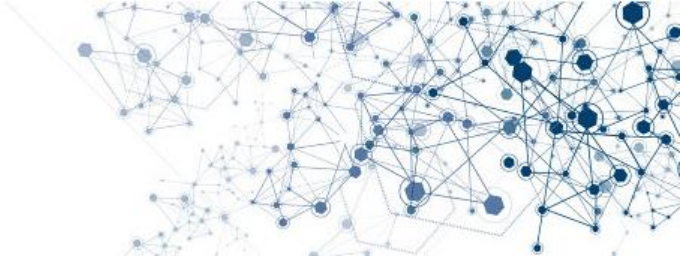
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**Presented at FloCon2018**  
**9 January 2018**



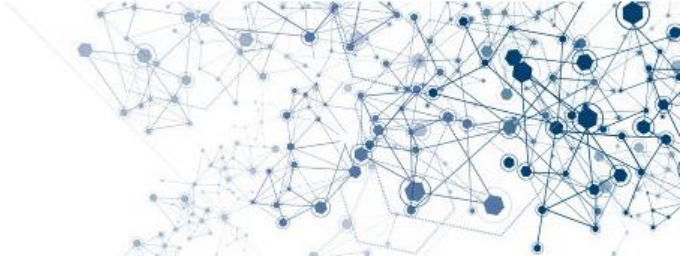
# Agenda

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



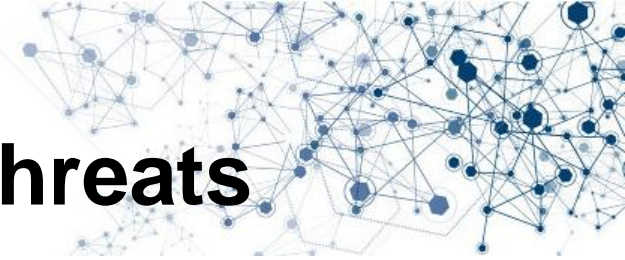
# Introduction

- **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

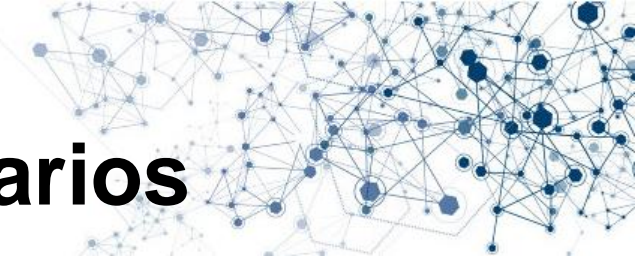
- Often associated with nation-state espionage
- Targets include private organizations & nation-states
- Low and Slow: Attack campaigns may last months
- Notoriously difficult to detect

(Preprint: A. Lemay, et al. 2018)



Image: <https://www.secureworks.com/blog/advanced-persistent-threats-apt-a>

# Simulated APT Scenarios



- **Simulation attributes**

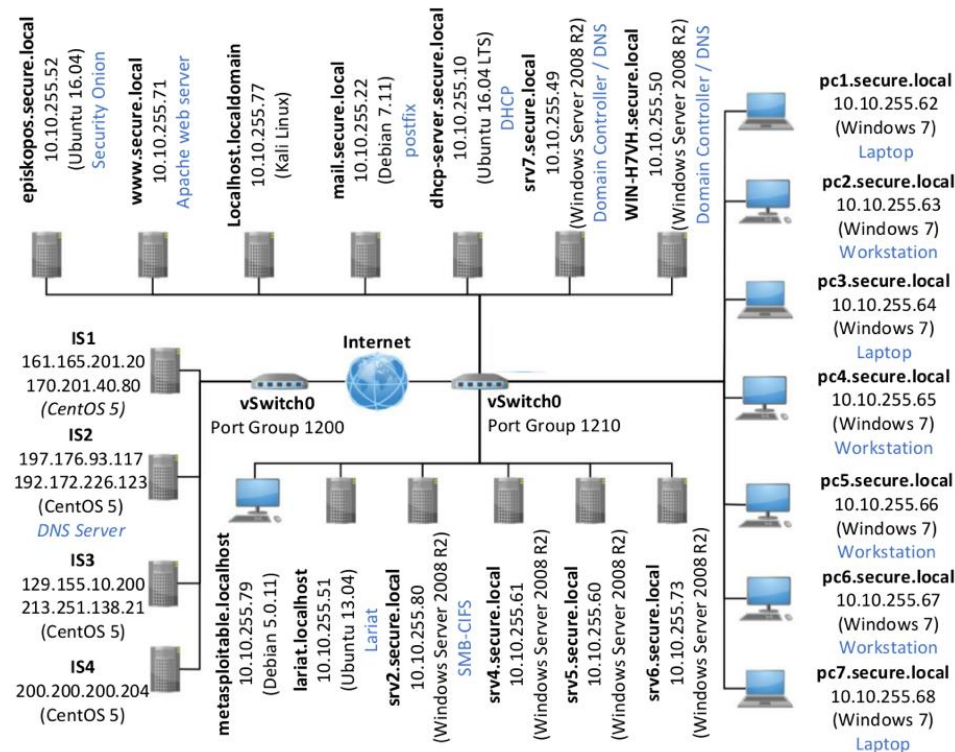
- Approx. 1 month of data per scenario
- Servers, laptops, switches
- Linux & Windows machines
- Normal & attacked behavior
- Generates IDS alerts and NetFlow traffic
- Detailed attack timeline

- **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



Network topology for simulations

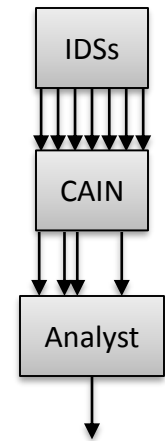


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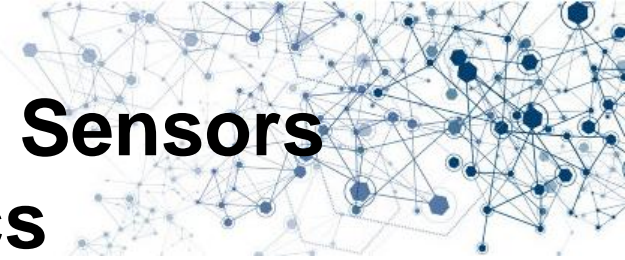
# Graph-based Approach

- **Fuses disparate IDSs**
- **Captures alert interdependencies**
- **Efficiently represents many alerts**
- **Robust to circumvention**
- **Unsupervised**
- **Facilitates causal analysis**
- **Optimal parameters determined automatically**

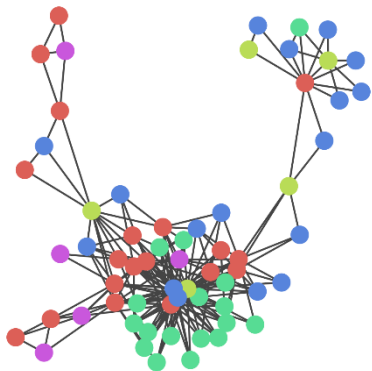




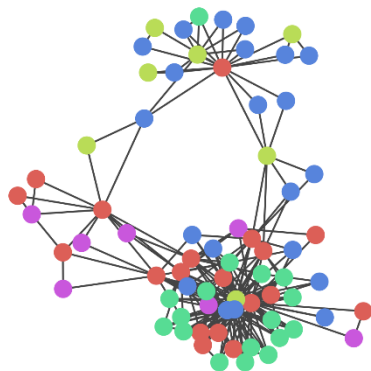
# Making Sense of Noisy IDS Sensors with Graph Analytics



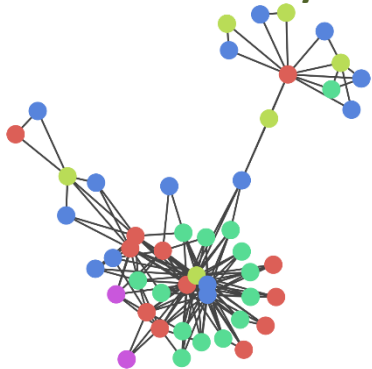
Normal Activity



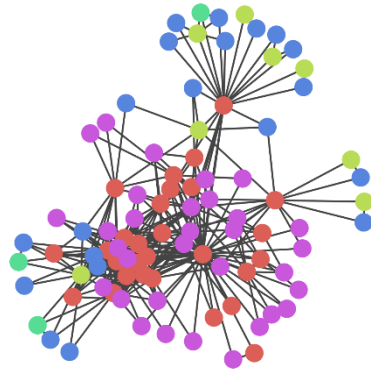
Normal Activity



Normal Activity



Hurricane Panda Attack



Alert Graphs from Hurricane Panda Simulation

- **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

*Akoglu et al. 2014*



# Alert Graphs

## 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]
    
```

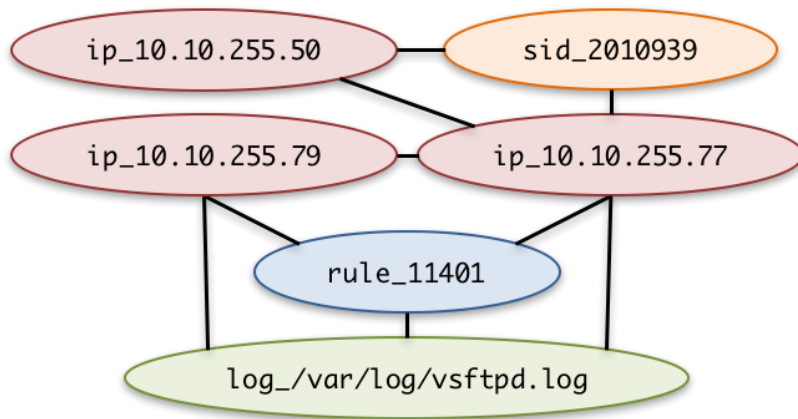
- **Graph of alerts  
(Not network topology)**

## Snort Alert (Network IDS)

```

11/30-15:32:15.407340 [**] [1:2010939:2] ET
POLICY Suspicious inbound to PostgreSQL port 5432
[**] [Potentially Bad Traffic] [Priority: 2] {TCP}
10.10.255.77:38989 -> 10.10.255.50:5432
    
```

## Alert Graph





# Alert Graphs

## OSSEC Alert (Host IDS)

```

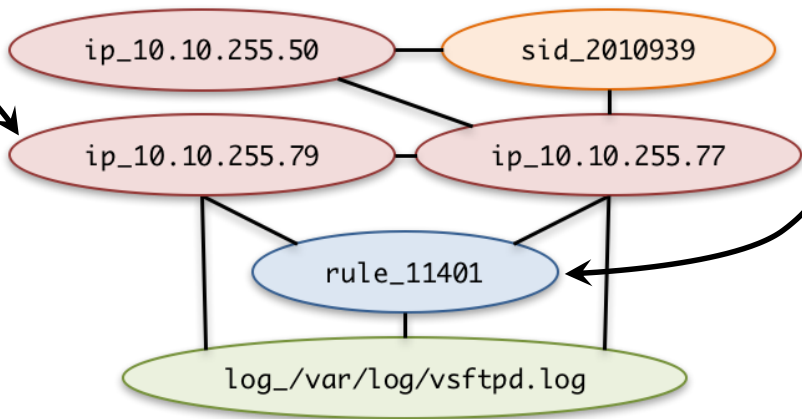
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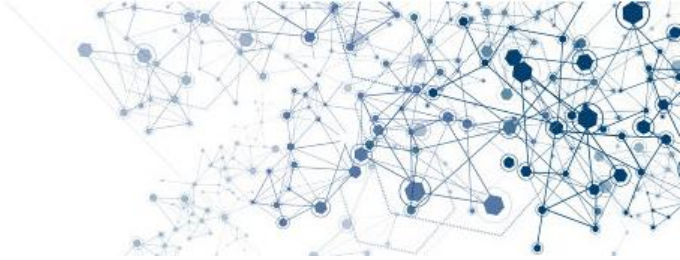
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## Alert Graph



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



# Alert Graphs

## OSSEC Alert (Host IDS)

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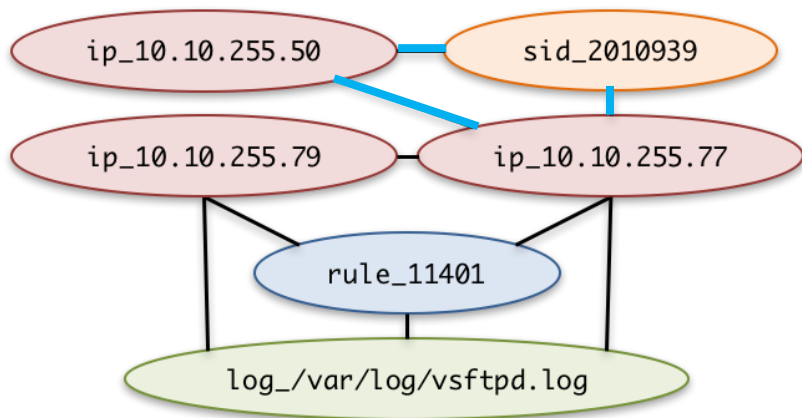
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## Alert Graph

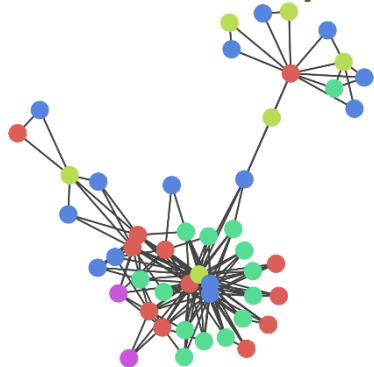


- **Graph of alerts (Not network topology)**
- **Alert properties become nodes**
- **Node colors indicate property type**
- **Edges connect nodes that co-occur in alerts**
- **Edges weighted by frequency of co-occurrence**

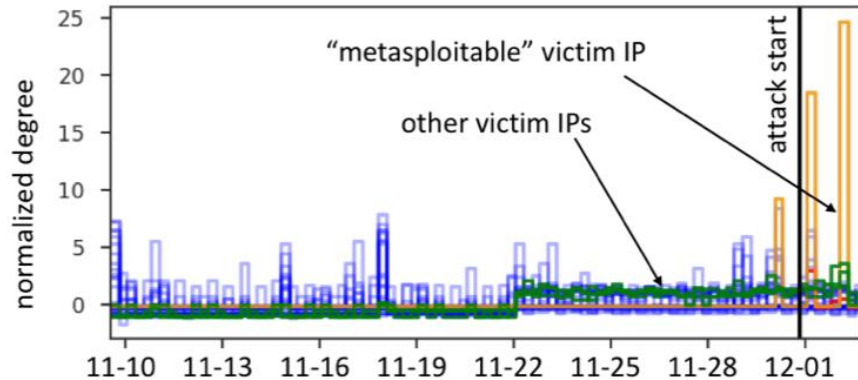
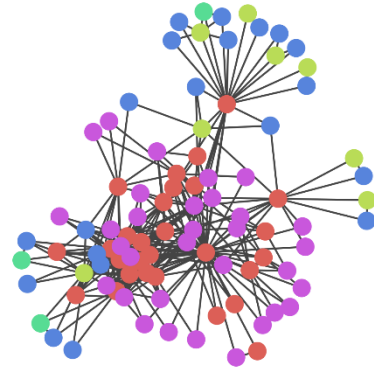


# Alert Graphs

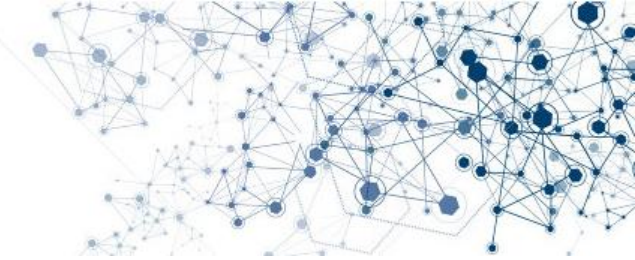
Normal Activity



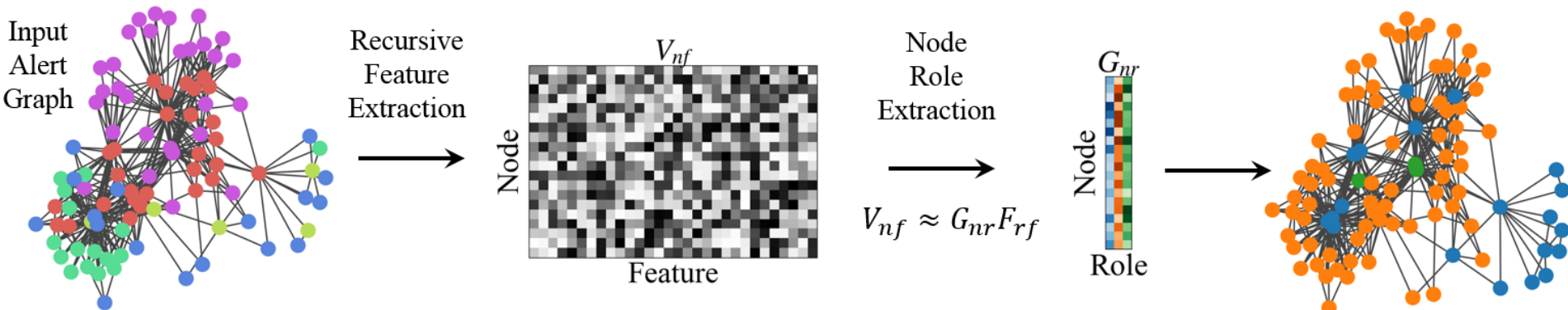
Hurricane Panda Attack



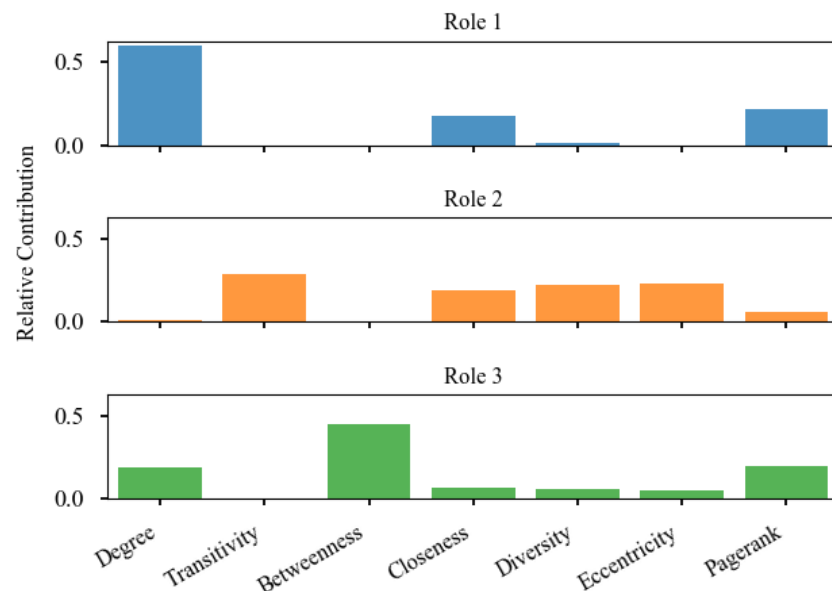
- **Cyber attacks change IDS alert logs**
- **Intuition**
  - Changes in alert logs modify alert graph
  - Anomalies in the graph features (properties) may indicate cyber attacks
- **Quick test**
  - Degree of IP nodes shows marked changes during simulated attack
  - But a single feature is likely insufficient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

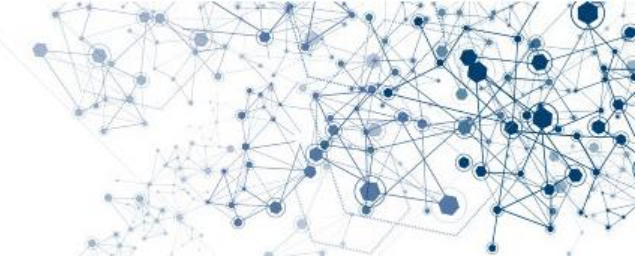


# Role Dynamics

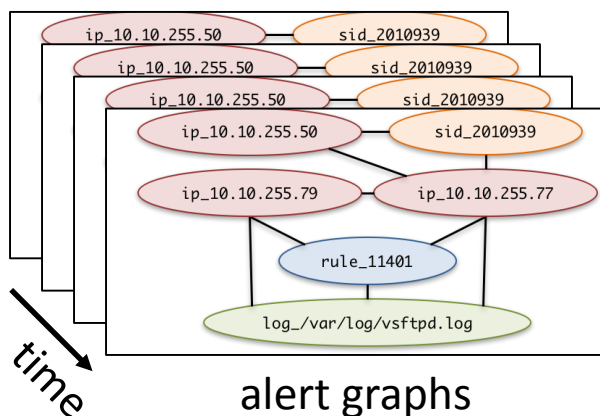


- Infeasible to model every feature of every node
- Instead, use graph-based anomaly detection algorithms
- Role dynamics (Rossi et al., 2012)
  - Collect features and factorize as roles
  - Roles provide a succinct, integrated summary across a large number of features
  - Output is probability of membership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



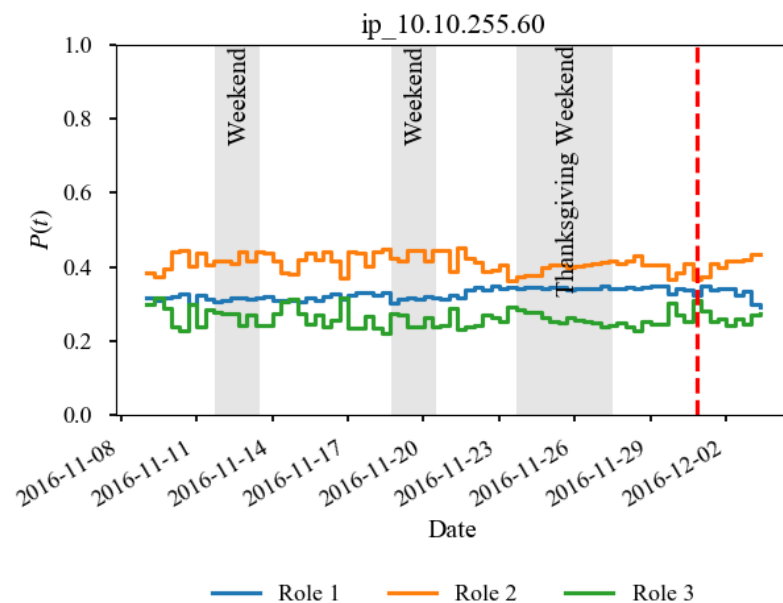
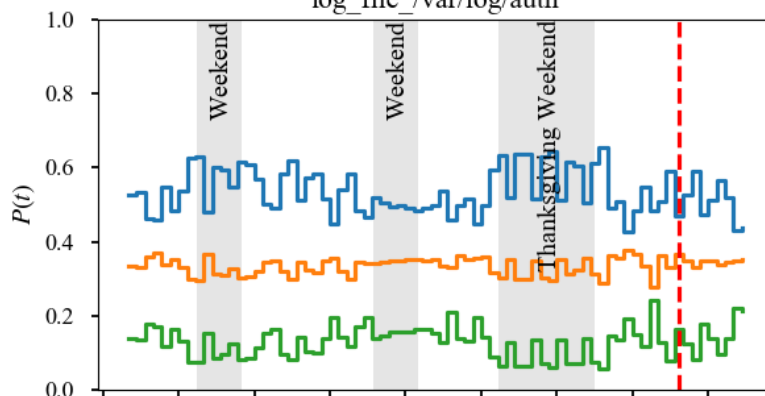


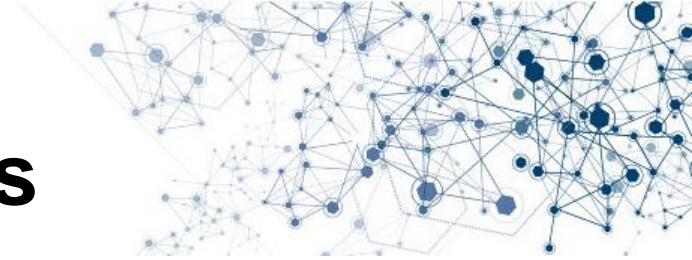
# Role Dynamics



- Infeasible to model every feature of every node
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  - 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
  - Track role memberships over time

Roles for nodes in Hurricane Panda simulation  
log\_file /var/log/auth

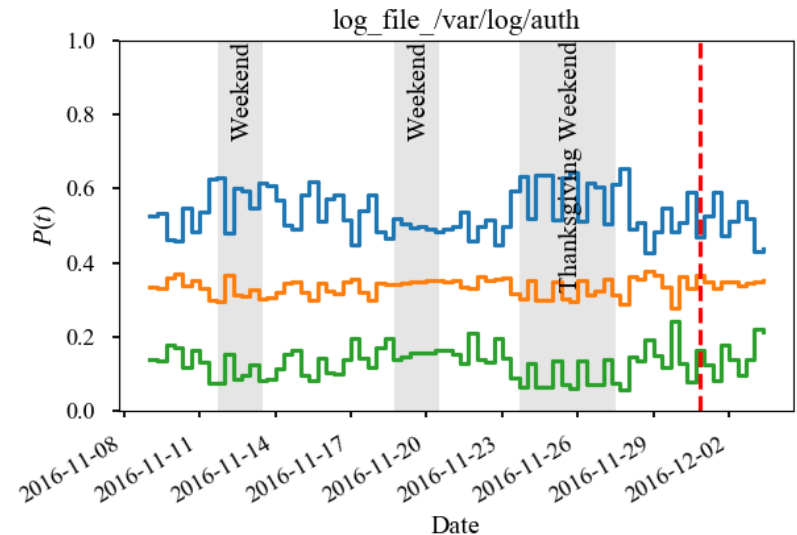




# Role Dynamics

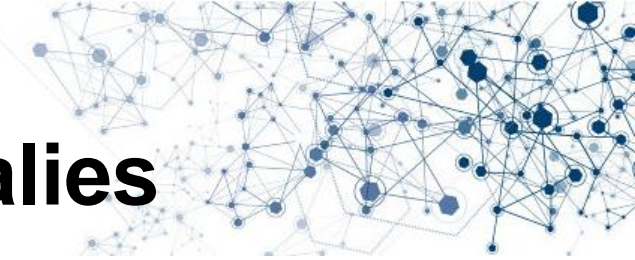
- **Why role dynamics?**

- 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



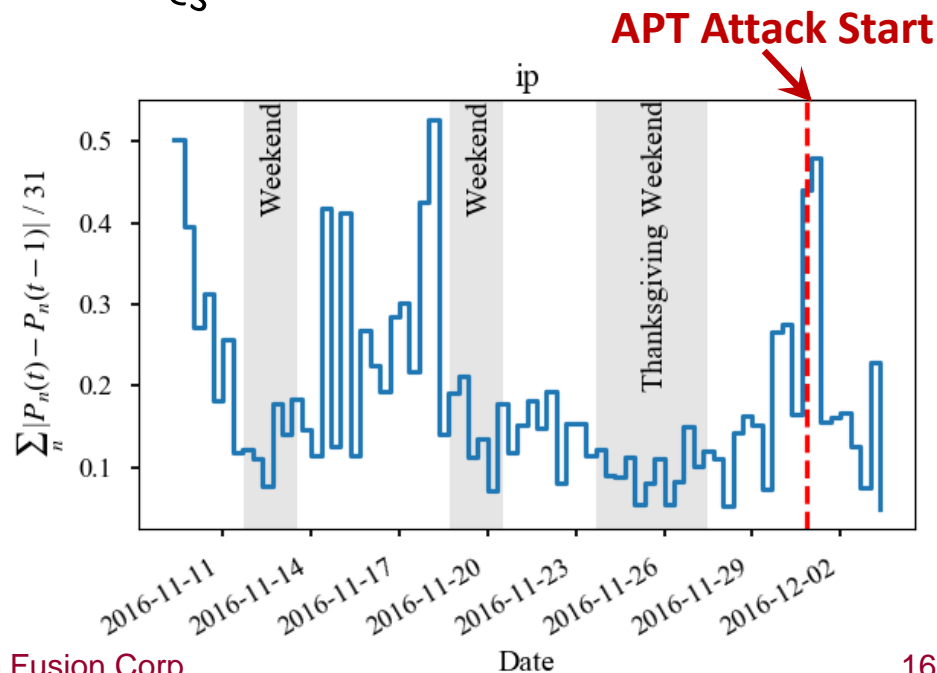
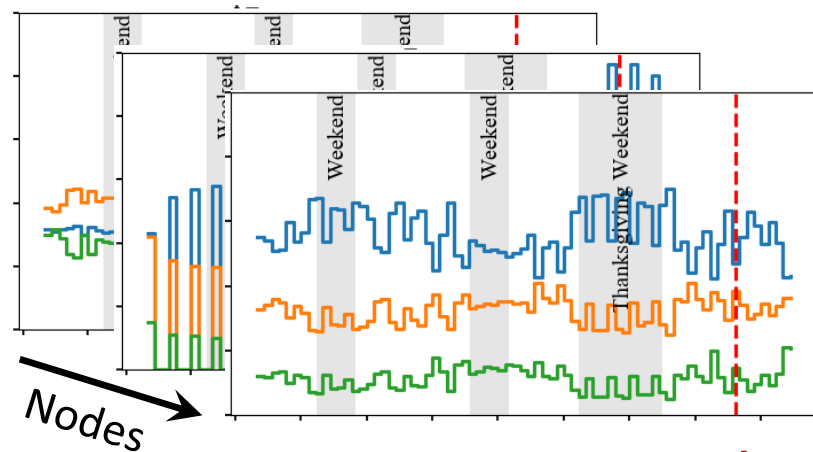


# Finding Role Anomalies

- **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



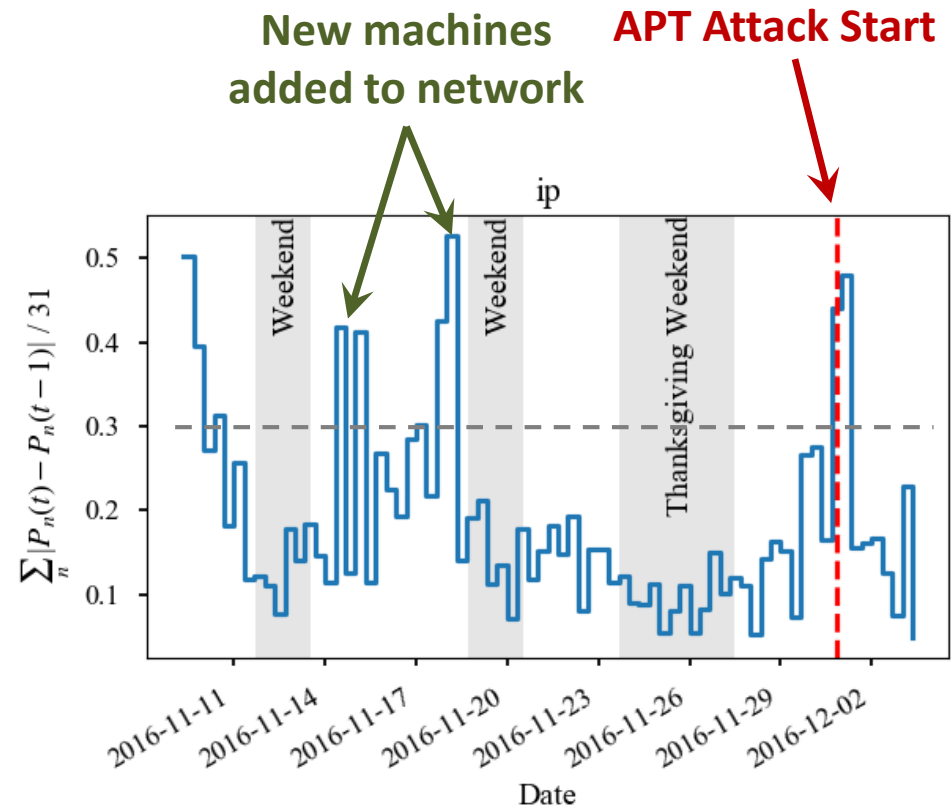
# Results: APT Scenario 1

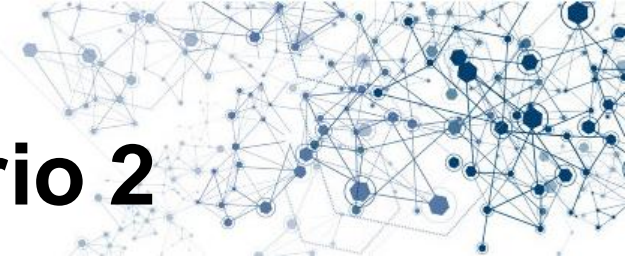
- **Hurricane Panda scenario**

- 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**

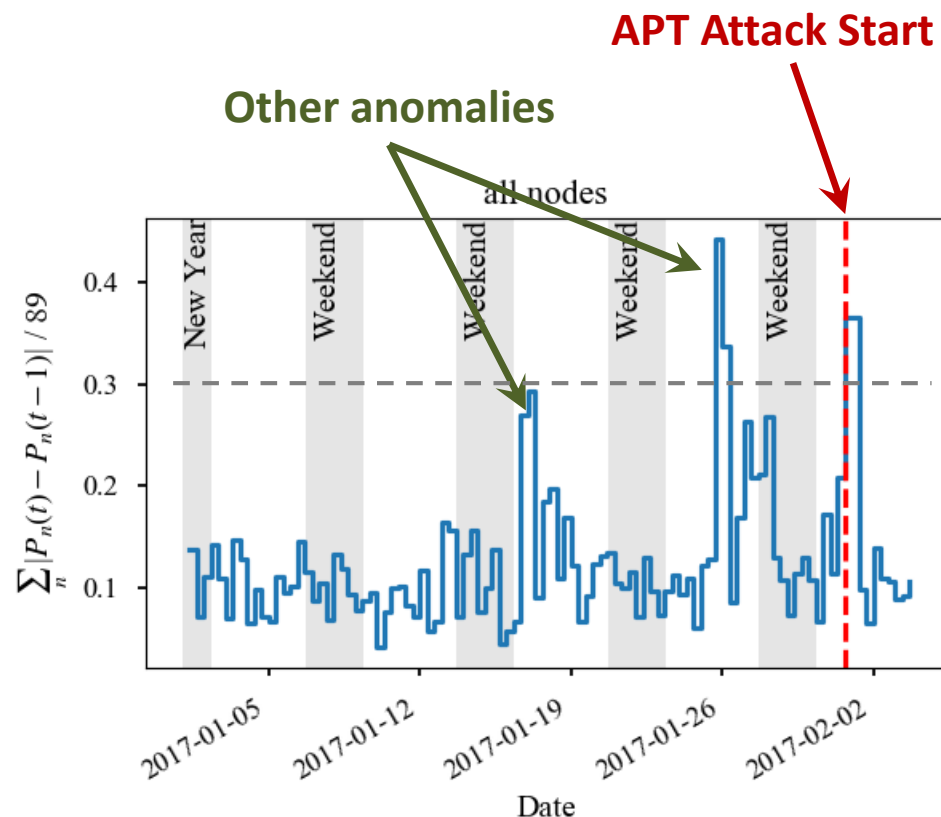
- Using threshold at 0.3, CAIN identified 4 anomalies
- Second two anomalies relate to machines coming online for the first time
- Last anomaly corresponds with the start of Hurricane Panda's attack





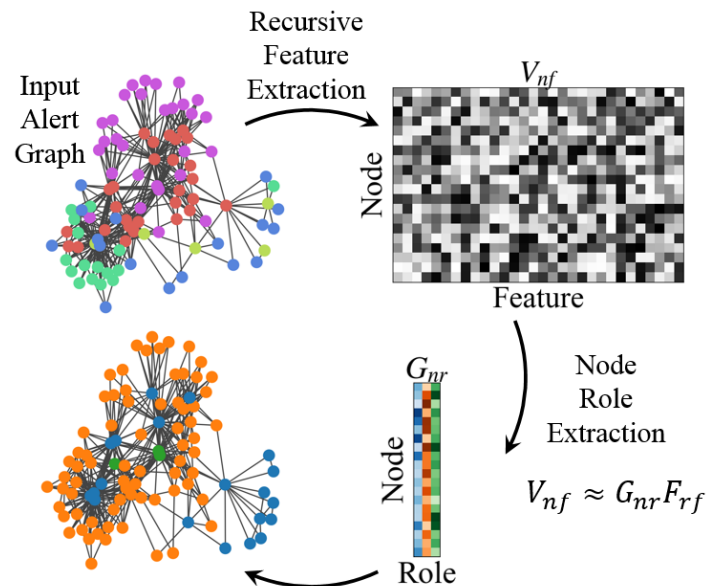
# Results: APT Scenario 2

- **Energetic Bear scenario**
  - Same network as Hurricane Panda
  - 1 Jan 2017 – 4 Feb 2017
  - 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

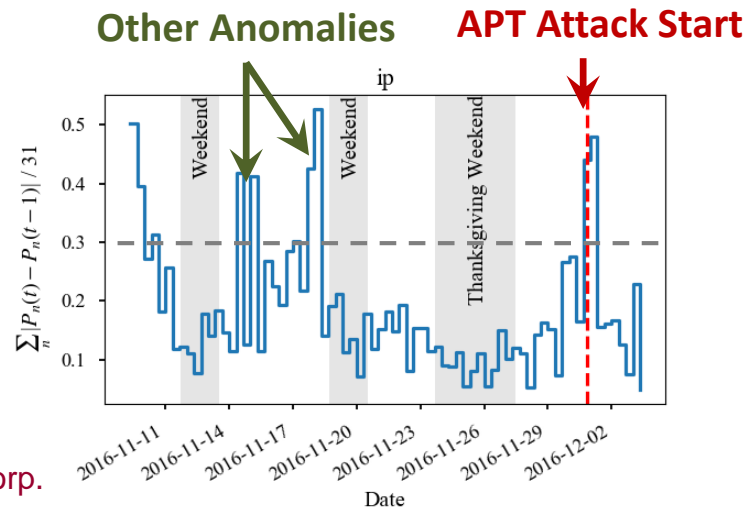


# Conclusions: Making Sense of Noisy IDS Sensors with Graph Analytics

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



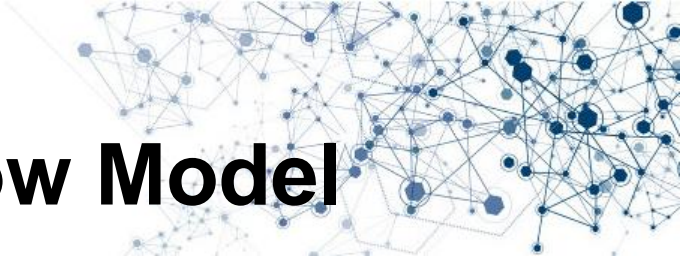
- **Success in 2 APT scenarios demonstrates:**
  - Robust to different types of APTs and attack vectors
  - Insensitive to IDS systems



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- **Bayesian Normalcy Modeling**
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# Bayesian Dynamic Flow Model

- **Unsupervised model of NetFlow traffic dynamics**
- **Assume data follows Poisson distribution**

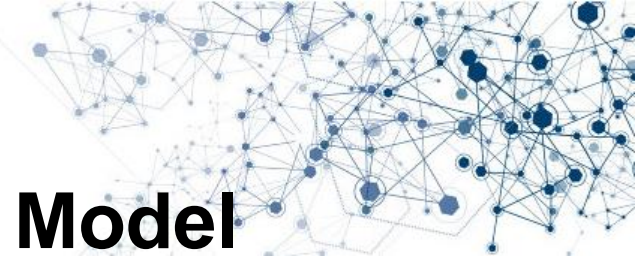
$$x_t \sim \text{Poisson}(\phi_t)$$

- **Model temporal evolution as Gamma-Beta discount model**

– Prior:  $x_t \sim P(\phi_t | x_{0:(t-1)}) = \Gamma(\delta_t r_{t-1}, \delta_t c_{t-1})$

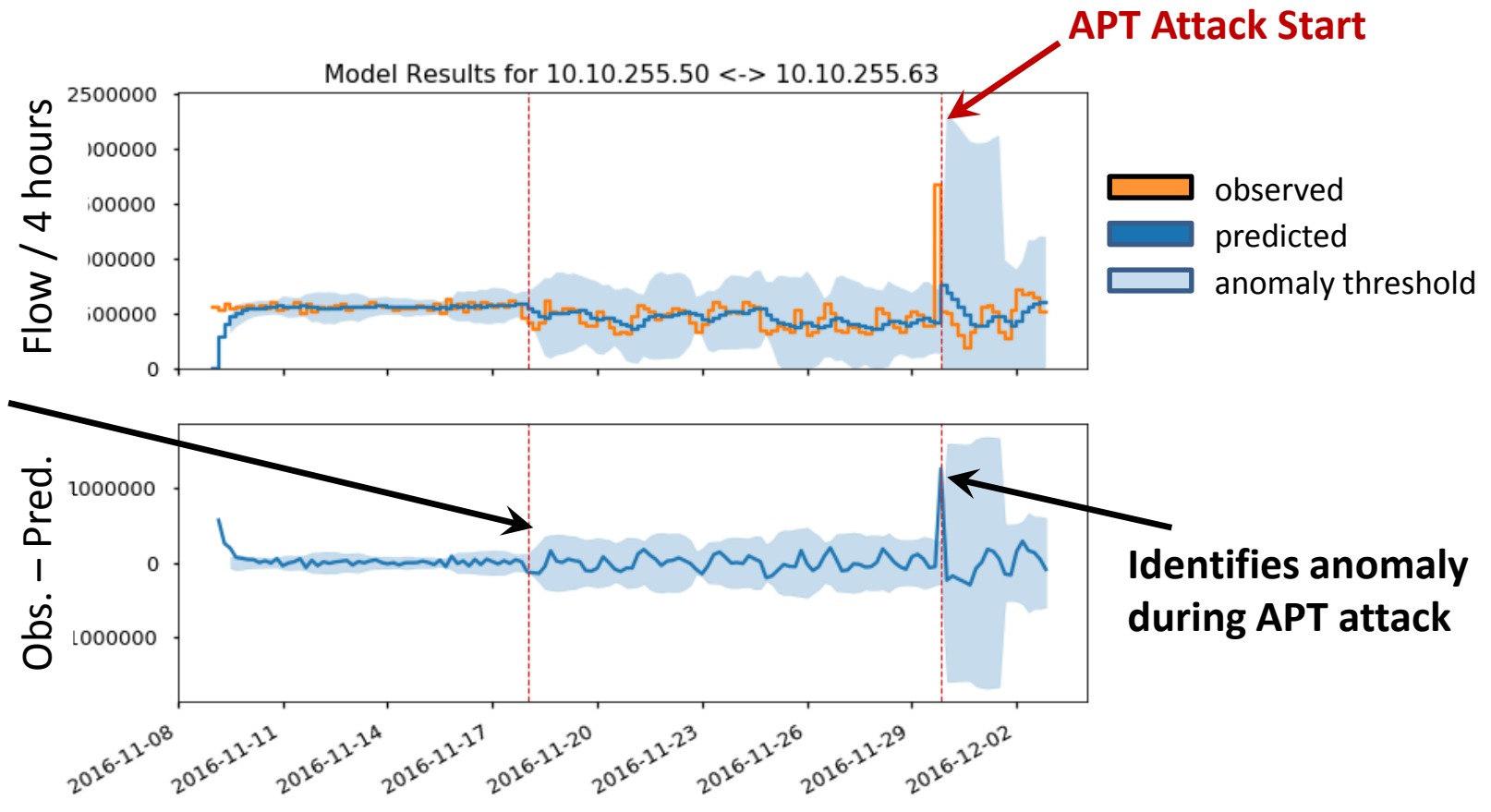
– Posterior:  $x_t \sim P(\phi_t | x_{0:t}) = \Gamma(\delta_t r_t, \delta_t c_t)$

(X. Chen, et al. 2016)



# Results

## Bayesian Dynamic Flow Model



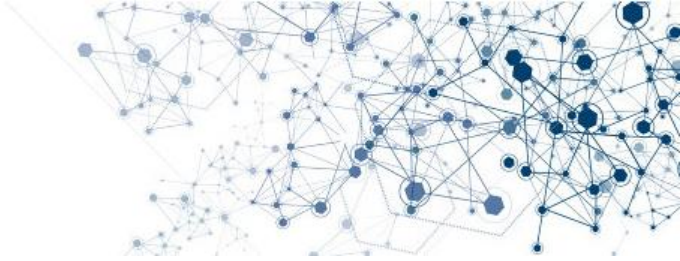
- Complementary to graph-based role-dynamics
- Multiple methods corroborate detection



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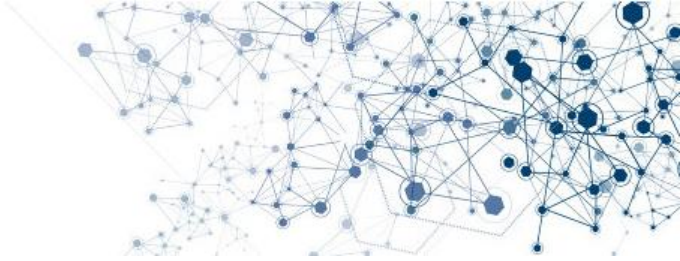
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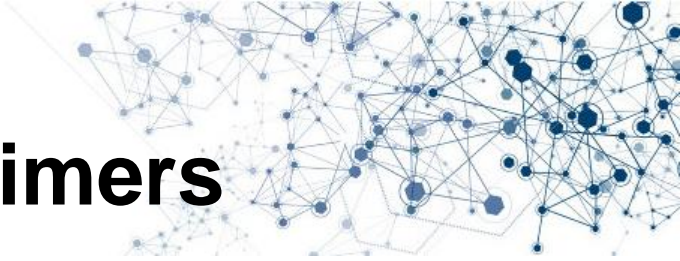
# Summary

- **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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