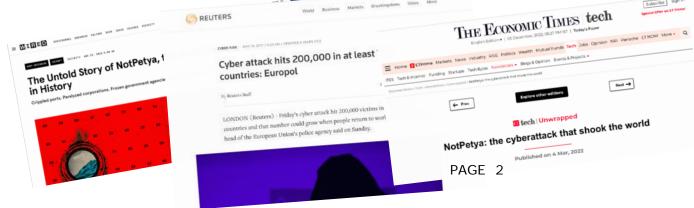
Soteria: An Approach for Detecting Multi-Institution Attacks

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Multi-institution Attacks (MIA)

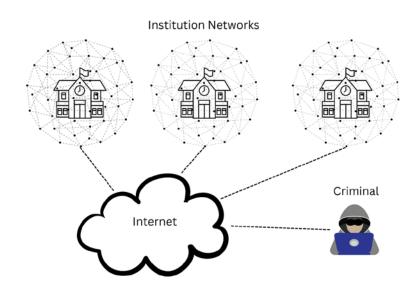
- An Attack targeting multiple institutions in a short time period
- Examples:
 - WannaCry affected 200,000 computers in 150 countries (2017)
 - NotPetya, estimated loss is \$10 billion (2017)
- Challenging to defend:
 - Vulnerabilities change quickly
 - Attacks happen quickly
 - Many existing/new threats in the wild





MIAs are Challenging in the Education Sector

- Large and constantly changing networks
- Low budget and understaffed teams
- Prime targets for MIAs
 - Cybercrime cost institutions an average of \$9.25 million in 2019
 - 46% of institutions reported attacks in 2017





Related Works

- Reconnaissance works:
 - Limited to detecting port scans
- Heavy Hitter detection:
 - Detecting hosts that communicate with large number of hosts
 - Limited to predicting the number of hosts
- Current approach relies on sharing intel (e.g. Virus Total)
 - Threat sharing delays
 - It requires cybersecurity experts time
 - Privacy constraints







Requirement of an MIA detection tool

- Accurately predict attacks
- Severity estimation
- Predicting the next victims of an attack





Soteria - the contribution

- A data analysis pipeline for detecting MIAs
- Uses graph analysis and ML
- Deployed as part of CANARIE IDS
- Overview of the results,
 - Able to predict MIAs
 - Predict future attacks with 95% recall rate
 - Estimates the severity of the attack with high accuracy
 - Predict the next targets of an attack with 95% recall rate
 - Detect attacks in the first 20% of their life span



Outline

- Motivation and Introduction
- Soteria design
 - Feature Extraction
 - Static Metrics
 - Dynamic Metrics
 - Attack detection
 - Severity Estimation
 - Next Target Prediction
- Evaluation
- Conclusion

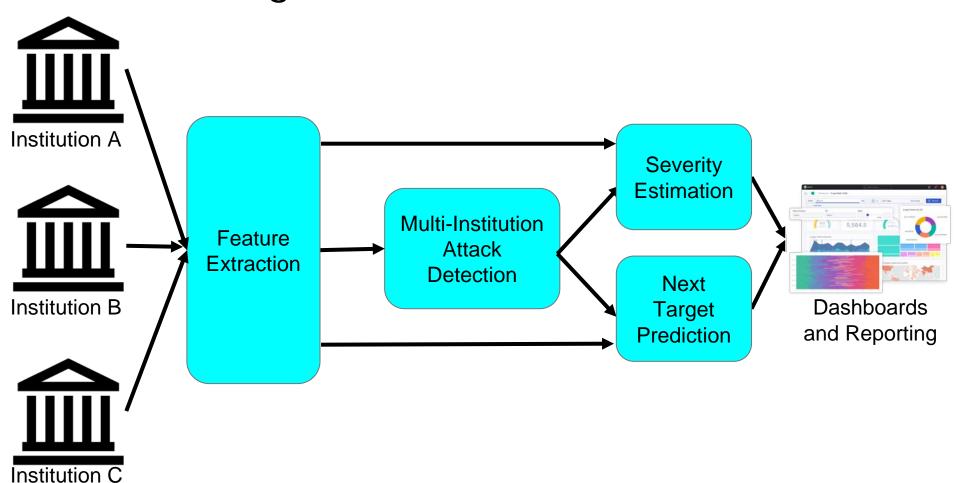


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Soteria design

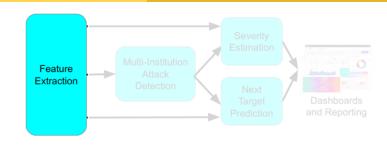




Feature Extraction

- Institution share zeek logs
- Input dataset from connection logs
 - id.orig_h: Source ip
 - id.resp_h : Destination ip
 - ts: Timestamp
 - local_orig: is the orig ip local
- Topological graphs are a natural representation for the dataset and the attack





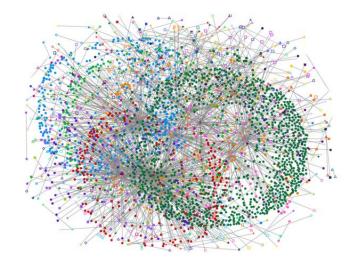


Feature Extraction



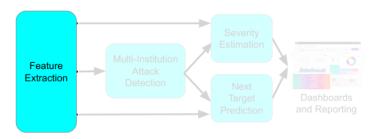
Challenge: Generating a graph from the dataset does not scale

- Graphs are massive
- Processing metrics is slow



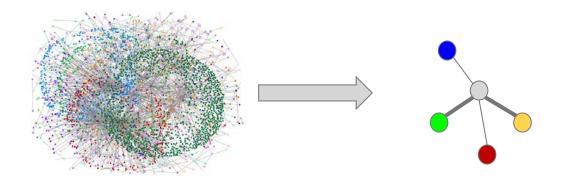


Feature Extraction



Solution: Graph compression without losing relevant information

- Removing connections initiated internally
- Each educational institute's IPs clustered into a single vertices
- Directed aggregate edge
 - With weights





Graph Creation

Feature Extraction

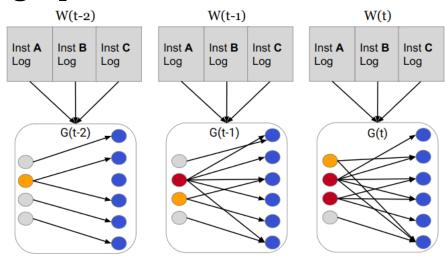
Multi-Institution Attack Detection

Next Target Prediction

Prediction

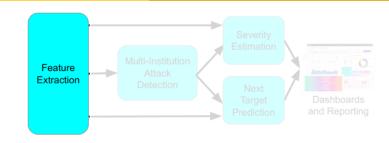
Next Target And Reporting

- Collect logs by time windows
- Windows have two variables:
 - Window length
 - Number of windows
- Create graph for each window



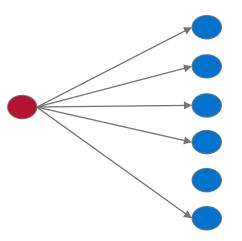


External IP Metrics



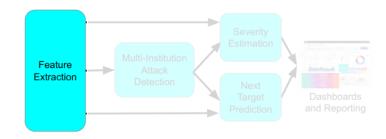
For each external IP in a time window:

- inst_count : Number of institutes targeted
- ip_count: Number of IPs targeted
- conn_count: Number of connections attempted
- total_count: Total number of institutes targeted
- V(Adj): List of the institutions targeted in current window
- V(cumltv): Cumulative list of all institutions targeted until now

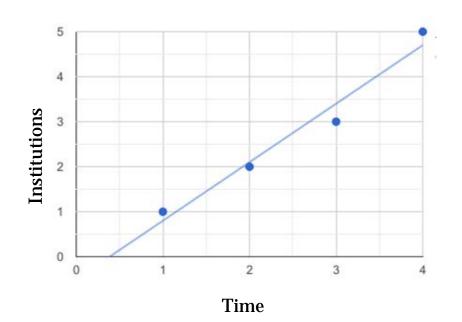




Dynamic Feature Extraction



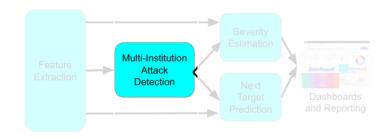
- For each metric
 - Capture growth across windows
- Use linear regression:
 - Predict an attack
 - Get growth metric

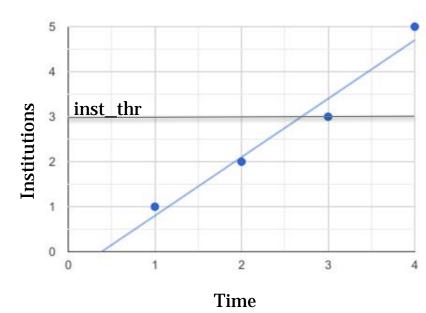




Attack Detection

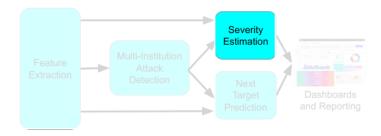
- An IP is identified as an attacker if its total_count exceeds a threshold (inst_thr)
- Predict an Attack:
 - If the Linear Regression line of total_count exceeds the inst_thr



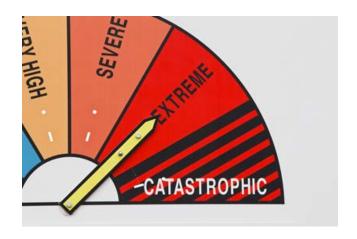




Severity Estimation

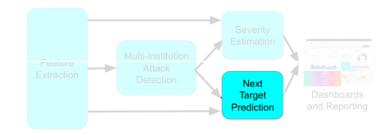


- Calculate a severity indicator in the range of [0,1]
 - Normalizing each feature in the range [0,1]
 - Robust scaling: to mitigate outliers stretching boundaries
- Sort these threats using severity indicator

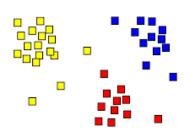




Next Target Prediction

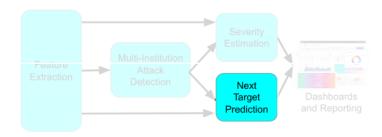


- Can we predict their path?
- Hypothesis:
 - Attackers follow a pattern in their movement.
 - Institute types are targeted together due to:
 - Service types
 - Security standards
 - Size of networks
 - etc...

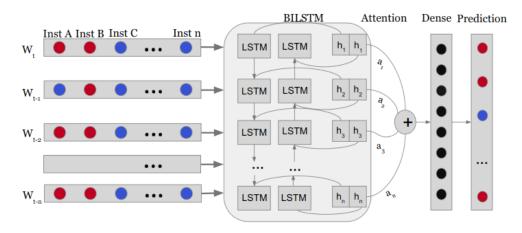




Next Target Prediction



- Bidirectional LSTM with Attention
- Benefits:
 - Learns relationship between institutions
 - Arranges windows in sequence and learns attack sequence
 - In both directions
 - Captures growth or decline of attack





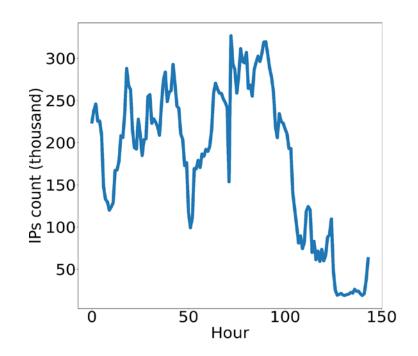
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Evaluation (Data Used)

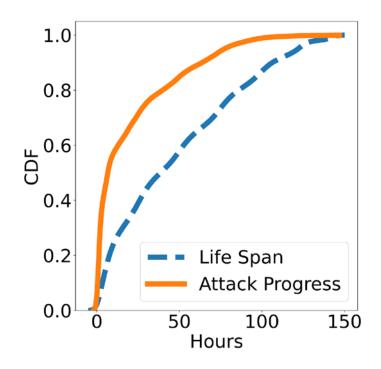
- 6 days of data
- 25th 30th of Jan 2022
- 52 institutions
- 12 million external IPs
 - 2.7 million are attackers
- External IPs count





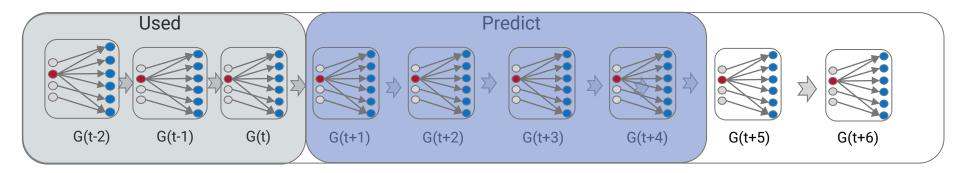
Evaluation (MIA Lifespan and attack progress)

- CDF of the MIA lifespan
 - 70% of attackers live 3 days or less
 - 50% live a day or less
- CDF of attack progress
 - When are they first targeted
 - Attacker contacts 70% of targets within the 1st day





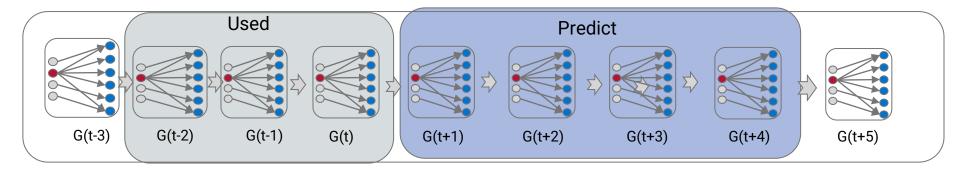
Evaluation (Life cycle of experiments)



- We divide time into windows example:
 - Window size is 6 hours
- We use 3 windows to predict attacks in the next 4 windows



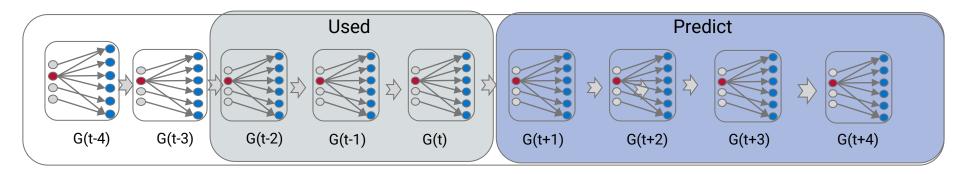
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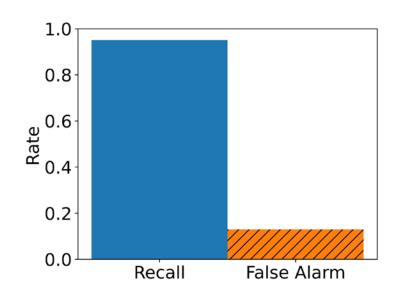
Evaluation (Metrics)

- Metrics used:
 - Recall = True Positives / (True Positives + False Negatives)
 - False Alarm = False Positive / (True Negatives + False Positives)
- Aggregated results
 - We take the cumulative results of all the runs
 - In all runs, has the model been able to predict that an institution will be reached.



Evaluation (can it detect future Multiinstitution attacks?)

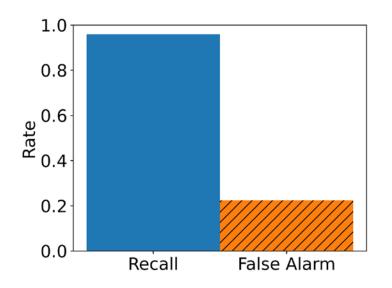
- 3 hour windows with 3 windows
- Soteria predict future attacks well:
 - **Recall 95%**
 - False alarm 15%





Evaluation (can it find next target?)

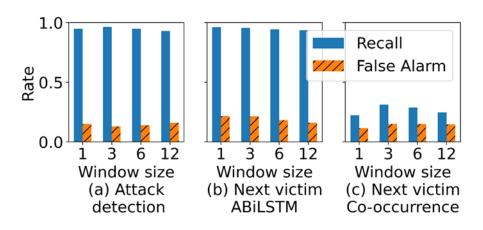
- 3 hour windows with 3 windows
- Soteria predicts effectively the next target:
 - Recall of 97%
 - False Alarm of 20%

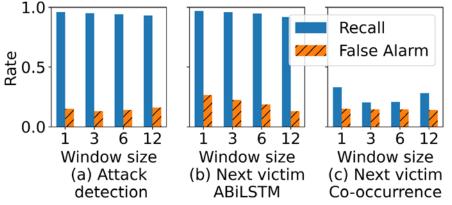




Evaluation (Which window size and count is best?)

- Evaluated multiple window sizes
 - Fixed window count (3 windows)
 - Fixed the lookback time (24 hours)
- Slightly better with:
 - Smaller windows
 - Smaller number of windows

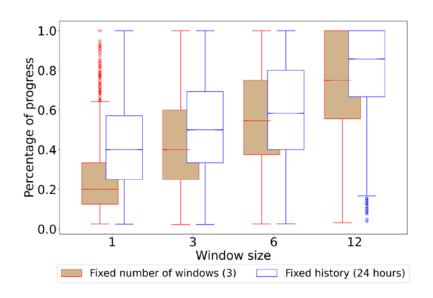






Evaluation (How soon can Soteria predict an attack?)

- Evaluated using all the window size and count combinations used previously
- Soteria can predict an attack is happening at 20% progress
- Smaller windows with less windows predicts faster.
 - 1 hour windows provide up to 4x earlier detection





Insights

- External IPs contacting more than 2 institutions are most likely involved in an attack
- A simple linear regression model is highly effective in predicting future attack
- To accurately predict the next target of an attack we need to learn:
 - The relationships between institutions
 - The sequence of the attack
 - The level of activity of an attacker



Conclusion

- Educational Institutions have huge networks and inadequate cyber security resources.
 - Attackers take advantage of this.
- Proposed model is able to:
 - Detect multi-institutional attacks
 - Current and future
 - **Recall 95%**
 - False Alarm 15%
 - Able to predict institutions targeted
 - Recall 97%
 - False Alarm 20%
- Currently deployed in the CANARIE IDS

