CE 815 – Secure Software Systems

Causal Analysis (Poirot)

Mehdi Kharrazi Department of Computer Engineering Sharif University of Technology



Acknowledgments: Some of the slides are fully or partially obtained from other sources. A reference is noted on the bottom of each slide, when the content is fully obtained from another source. Otherwise a full list of references is provided on the last slide. Thanks to Zahra Fazli for the help on the slides.

Cybersecurity Stats in 2022



- An estimated 2,200 cyberattacks per day.
- 255 million phishing attacks occurring in a six-month span, with over 853,987 domain names reported for attempted phishing.
- 2.8 billion malware attacks launched in the first half of 2022 alone.
- 60% more malicious DDoS attacks occurring in the first six months of 2022 than the entirety of 2021.
- 1.51 billion IoT breaches were reported in the first six months of 2022.
- More than 500,000 users were negatively impacted by malicious mining software.
- 92% of malware was successfully delivered via email.
- 71% of organizations worldwide became victims of ransomware at least once.

Biggest Data Breaches in 2022



- Twitter was accused of concealing data breaches that impacted millions of users' data.
- More than 1.2 million credit card numbers were leaked on the hacking forum BidenCash.
- 11 million people were impacted by the Optus personal and medical cyberattack.
- Threat actors attempted to sell the data of 500 million WhatsApp users on the dark web.
- Both Uber and Rockstar had their internal servers compromised.
- A student loan breach released 2.5 million social insurance numbers.

Cybercrime Cost





https://www.independent.co.uk/advisor/vpn/cybercrime-statistics

CE 815 - Secure Software Systems

Advanced Persistent Threats Attacks





A Big Problem Affecting Many Nations and Industries

Initial Access Execution Persistence Privilege Escalation
Intrusion
Lateral Movement Discovery Credential Access Defense Evasion
Active Breach
Collection Command and Control Exfiltration Impact

Preparation

Long Duration and Stealthy

Fall 1403



- Targeted cyber attacks on organizations getting more sophisticated and stealthy.
 - Goal: to steal data, disrupt operations or destroy infrastructure.
- APTs combine many different attack vectors each appearing in some log sources.
- Firewall, IDS/IPS, Netflow, DNS logs, Identity and access management tools.
- Might occur over a long duration.
- Correlating heterogeneous alarms using heuristics like timestamp is not so effective Lacking the full picture (root cause, affected entities, etc.).

Evidence to investigate the attack



• System Audit log : ETW , Auditd , Sysmon , Sysdig

{"MSec": "166.6093", "PID": "1004", "PName": "msvsmon", "TID": "15336", "EventName": "FileIO/Read", "FileName": "C:\\Users\\Administrator\\Desktop\\ConsoleApp1\\ConsoleApp1\\bin\\x64\\Release\\System.Runtime.CompilerServices.Unsafe.dll", "Offset": "0", "IrpPtr": "0xFFFF38FF04D2358", "FileObject": "0xFFFF38FF047B900", "FileKey": "0xFFFF9407EF3EF700", "IoSize": "23,600", "IoFlags": "395,520"} {"MSec": "597.7318", "PID": "4880", "PName": "pgAdmin4", "TID": "13740", "EventName": "Image/Load", "ImageBase": "0x00007FF9130F0000", "ImageSize": "0x0012A000", "ImageChecksum": "1,265,582", "TimeDateStamp": "-1,130,476,303", "DefaultBase": "0x00007FF9130F0000", "FileName": "C:\\Windows\\System32\\ole32.dll"} {"MSec": "953.0958", "PID": "6624", "PName": "SearchApp", "TID": "-1", "EventName": "TcpIp/Send", "size": "80", "daddr": "202.89.233.101", "saddr": "192.168.0.74", "dport": "443", "sport": "58,197", "startime": "3,607,236", "endtime": "3,607,237", "seqnum": "0", "connid": "0x0000000"}

An example of windows ETW

Provenance Graph



- Use Provenance Graph to enable alert correlation for attack campaign detection.
- Vertices:
 - system entities (socket, process, file, memory, etc.), and agents (user, groups, etc.)
- Edges: system calls (causal dependencies or information flow)
- Leverage the full historical context of a system.
- Reason about interrelationships between different events and objects.

Detect APT Attacks with Provenance Graph





With data provenance, we can capture **full historical context** and all **casual relationships** among system subjects (e.g., process) and objects (e.g., files). **Poirot: Aligning Attack Behavior with Kernel Audit Records for Cyber Threat Hunting**, S. M. Milajerdi, B. Eshete, R. Gjomemo, V. N. Venkatakrishnan, CCS, 2019.

Threat Hunting



- IOC: Indicators of Compromise (IOCs) related to an Advanced Persistent Threat (APT) detected in an organization.
- Post-detection, a prevalent query among security analysts is the potential targeting of their enterprise by the APT.
- The endeavor to ascertain if the enterprise was targeted, termed as Threat Hunting.
- Requires extensive and complex searches plus analysis on enterprise's host and network logs.
- Identifying entities from IOC descriptions in logs and evaluating the likelihood of the APT's successful infiltration.



- Design approaches to link related IOCs over long attack durations, enabling search among millions of log events.
- Ensure sound identification of attack campaigns despite mutated artifacts, and uncover the entire threat scenario.
 - Attacker might have mutated the artifacts like file hashes and IP addresses to evade detection.
- Facilitate timely understanding and reaction to threats by minimizing false positives and enabling prompt cyber-response operations.

Threat Hunting Limitations



- Information often shared via Cyber Threat Intelligence (CTI) reports in various formats like natural language, structured, and semi-structured forms.
 - OpenIOC, STIX, and MISP standards to facilitate IOC exchange and adversarial TTPs (techniques, tactics, and procedures) characterization.
- Current threat hunting largely operates on fragmented views like signatures, file/process names, and IP addresses.

Poirot





Provenance Graph Construction (Gp)



- Determine APT actions in the system by modeling kernel audit logs.
- labeled, typed, and directed graph representation of kernel audit logs for efficient causality and information flow tracking.
- Nodes Representation: System entities involved in kernel audit logs like files and processes.
- Edges Representation: Information flow and causality among nodes, considering direction.
- Supports kernel audit logs from Windows, Linux, and FreeBSD, constructing an in-memory provenance graph with efficient searching features like fast hashing and reverse indexing for process/file name to unique node ID mapping.



Provenance Graph Construction (Gp)



Query Graph Construction (Gq)



- IOCs and relationships among them are extracted from CTI reports related to known attacks, obtained from various sources like security blogs, threat intelligence reports, and forums.
- Automated tools help in initial feature extraction to generate query graphs, with manual refinement by security experts to reduce noise and enhance quality.
- The behavior from CTI reports is modeled as a labeled, typed, and directed graph, with entities transformed into nodes and relationships into directed edges.



Example: Report on DeputyDog malware

Upon execution, 8aba4b5184072f2a50cbc5ecfe326701 writes "28542CC0.dll" to this location: "C:\Documents and Settings\All Users\Application Data\28542CC0.dll". In order to maintain persistence, the original malware adds this registry key: "%HKCU%\Software\Microsoft\Windows\CurrentVersion\Run\ 28542CC0". The malware then connects to a host in South Korea (180.150.228.102).



Graph Alignment



- Aligning query graph G_q representing attack, with provenance graph G_p representing system activity.
- Matching single edges in G_q to paths in G_p , critical for algorithm design to handle noise added by attackers.
- Existing graph matching problems are NP-complete, with practical limitations in threat hunting context.
 - Hence, finds possible candidate alignments, expands search from high likelihood seed nodes, employing a novel metric called influence score to prioritize flows.
 - Upon alignment, a score representing similarity is calculated; if above a threshold, an alert is raised for analysts, otherwise, the process iterates with the next seed node candidate.





Fig. 3: Simplified Provenance Graph (G_p) , Query Graph (G_q) , and two sample graph alignments $(G_q :: G_p)$. Node types are shown with different shapes, and possible alignments for each node is shown with the same color. The numbers on the edges are merely to illustrate possible paths/flows and do not have additional meaning.



- Two Types of Alignments: Node alignment (between two nodes in different graphs) and graph alignment (a set of node alignments).
- Node Alignment Example: A node representing a commonly used browser in G_q and a node representing a Firefox process in G_p.
- Many-to-Many Relationship from $V(G_q)$ to $V(G_p)$, indicating multiple possible alignments.
- Find the best possible graph alignment among candidate graph alignments.
- Determine the best candidate alignment based on the number of aligned nodes and correspondence of flows to edges in G_q .



- Path scoring function to quantify the "goodness" of a graph alignment.
- Likelihood of an attacker producing a flow between nodes.
- Two flows from node firefox2 to %registry%\firefox in graph G_p, with different likelihoods based on attacker control.
- Not dependent on flow length but on the number of processes and distinct ancestors in the process tree.
- Robust against evasion attempts, as activities adding noise have the same common ancestors unless attacker incurs higher compromise costs.

Provenance Graph Construction (Gp)







- C_{min}: Minimum number of distinct compromises needed to create a flow from node i to node j.
 - Common Ancestor: C_{min} value of 1 if all processes in a flow share a common ancestor.
 - Multiple Ancestors: Higher C_{min} values indicate more compromises and a harder flow for attackers.
- Assumption that attackers are unlikely to compromise many processes due to resource constraints.
 - C_{thr} Limit: A threshold limiting C_{min} values to identify likely attacker-initiated flows.
- Influence Score: Inverse of C_{min}, higher values indicate easier control by an attacker.
- Maximum and Minimum Scores: Scores range from 1 (easy control) to 0 (no flow exceeding C_{thr}).



- S(G_q ::G_p) calculates alignment score based on influence scores.
 - Sum of influence scores normalized by maximal possible value.
 - Higher S(G_q ::G_p) value indicates more node alignments and similar flows under potential attacker control.
- Score Range: Value between 0 and 1, with 1 indicating high likelihood of attacker control.
- Alarm Threshold: Predefined threshold τ to trigger an alarm.
- Threshold Calculation: τ determined based on maximum number of distinct entry points an attacker is likely to exploit.
- Alarm Condition: Alarm raised if $S(G_q :: G_p) \ge \tau$.



- Maximize alignment score by finding G_q ::G_p in a large provenance graph G_p
 - Size of G_p reaching millions of nodes and edges.
- Step 1 (Find Candidate Node Alignments):
 - Search G_p nodes for candidate alignments for each G_q node.
 - Candidate alignment based on node name, type, annotations.
 - Initial step focuses on nodes in isolation without path/flow information.



- Step 2 (Selecting Seed Nodes):
 - Identify starting points based on likely attack activities having fewer alignments.
 - Sort nodes by increasing order of candidate alignments and select seed nodes with fewest alignments first.
- Step 3 (Expanding the Search):
 - From selected seed node, iterate over all aligned nodes in G_p initiating graph traversals to find other aligned nodes.
 - Stop search expansion along a path once influence score reaches 0 to reduce search complexity.
 - Multiple forward/backward tracking cycles may be needed based on G_q shape.
 - Repeat traversals from nodes adjacent to unvisited but previously visited nodes until all G_q nodes are covered.



- Step 4 (Graph Alignment Selection):
 - Produce final result or iterate search from Step 2 if no result is found.
 - Identify a subset of candidate nodes in G_p for each node in G_q .
 - Determine total possible graph alignments based on candidate alignments per node.
 - Maximize alignment score by starting from a seed node, select node in G_p maximizing alignment score contribution, and fix this node alignment. Follow edges in G_q to fix alignment of additional nodes, selecting those maximizing score contribution.
- Selection Function
 - Approximates each alignment's contribution to final alignment score, aiming for highest contribution.
 - Evaluation reveals attack graph usually found within the first few iterations.

Evaluation



- Experiment 1: Utilized DARPA Transparent Computing (TC) program scenarios, simulating adversarial engagements in an enterprise network setting.
- Experiment 2: Tested Poirot on real-world incidents replicated from publicly available threat reports in a controlled environment.
- Experiment 3: Assessed Poirot's false signal robustness in an attack-free dataset.
- C_{thr} set to 3 across experiments, influencing false positives/negatives rate.
- Manual analysis of matched attack subgraphs to validate correct pinpointing of actual attacks in query graphs.

Evaluation on DARPA TC Dataset



- Experiment Setup: Utilized a dataset from DARPA TC program's red-team vs. blueteam adversarial engagement, with various servers and benign activities simulated.
- Attack Scenarios Evaluated: Ten scenarios across BSD, Windows, and Linux systems.
- BSD Attacks: Executed on a back-doored Nginx server on FreeBSD 11.0 (64-bit).
- Windows Attacks: Win-1 involved a phishing email with malicious Excel macro; Win-2 exploited a vulnerable Firefox browser on Windows 7 Pro (64-bit).
- Linux Attacks: Conducted on Ubuntu 12.04 (64-bit) and 14.04 (64-bit); Linux1&3 had in-memory browser exploits, while Linux2&4 involved malicious browser extensions.



Evaluation on DARPA TC Dataset (Con't)

Scenario	subjects ∈	objects ∈	$ E(G_q) $	$ F(G_q) $	
	$ V(G_q) $	$ V(G_q) $			
BSD-1	4	9	19	81	
BSD-2	1	7	10	32	
BSD-3	3	18	34	159	
BSD-4	2	8	13	43	
Win-1	13	8	26	149	
Win-2	1	13	19	94	
Linux-1	2	9	19	62	
Linux-2	5	12	24	112	
Linux-3	2	8	22	48	
Linux-4	4	11	22	96	



Evaluation on DARPA TC Dataset (Con't)



Fig. 4: Cumulative Distribution Function (CDF) of number of candidates in $|G_p|$ for each node of $|G_q|$. From left to right: BSD, Windows, and Linux Scenarios.



Evaluation on DARPA TC Dataset (Con't)



Fig. 5: Query Graph of Scenario: Linux-2 (on the left) and its Detected Alignment (on the right).

Evaluation: real-world incidents



Malware	Report	Vaar	Reported	Applyzed Malwara MD5	Sample	Isolated	Detection Results			
Name	Source	Ical	Samples	Anaryzeu Marware MD5	Relation	IOCs	RedLine	Loki	Splunk	Poirot
njRAT	Fidelis [58]	2013	30	2013385034e5c8dfbbe47958fd821ca0	different	153	F+H	F+H	Р	B (score=0.86)
DeputyDog	FireEye [50]	2013	8	8aba4b5184072f2a50cbc5ecfe326701	subset	21	F×2+H+R	F×2+H	P+R	B (score=0.71)
Uroburos	Gdata [5]	2014	4	51e7e58a1e654b6e586fe36e10c67a73	subset	26	F+H	F+H	R	B (score=0.76)
Carbanak	Kaspersky [22]	2015	109	1e47e12d11580e935878b0ed78d2294f	different	230	-	PE	S	B (score=0.68)
DustySky	Clearsky [65]	2016	79	0756357497c2cd7f41ed6a6d4403b395	different	250	-	-	-	B (score=1.00)
OceanLotus	Eset [6]	2018	9	d592b06f9d112c8650091166c19ea05a	subset	117	F+R	F+PE	P+R	B (score=0.65)
HawkEye	Fortinet [7]	2019	3	666a200148559e4a83fabb7a1bf655ac	different	3	-	PE	-	B (score=0.62)

Table 4: Malware reports. In the Detection Results, B=Behavior, PE=PE-Sieve, F=File Name, H=Hash, P=Process Name, R=Registry, S=Windows Security Event.

Evaluation: Benign Dataset



Scenario	Size on Disk	Consumption	Occupied	Log Duration	sub ∈	obj ∈	$ E(G_p) $	Search Time (s)
	(Uncompressed)	time	Memory	_	$ V(G_p) $	$ V(G_p) $		
BSD-1	3022 MB	0h-34m-59s	867 MB	03d-18h-01m	110.66 K	1.48 M	7.53 M	3.28
BSD-2	4808 MB	0h-58m-05s	1240 MB	05d-01h-15m	213.10 K	2.25 M	12.66 M	0.04
BSD-3&4	1828 MB	0h-21m-31s	638 MB	02d-00h-59m	84.39 K	897.63 K	4.65 M	26.09 (BSD-3), 1.47 (BSD-4)
Win-1&2	54.57 GB	4h-58m-30s	3790 MB	08d-13h-35m	1.04 M	2.38 M	70.82 M	125.26 (Win-1), 46.02 (Win-2)
Linux-1&2	9436 MB	1h-26m-37s	4444 MB	03d-04h-20m	324.68 K	30.33 M	51.98 M	1279.32 (Linux-1), 1170.86 (Linux-2)
Linux-3	131.1 GB	2h-30m-37s	21.2 GB	10d-15h-52m	374.71 K	5.32 M	69.89 M	385.16
Linux-4	4952 MB	0h-04m-00s	1095 MB	00d-07h-13m	35.81 K	859.03 K	13.06 M	20.72

Table 8: Statistics of logs, Consumption and Search Times.

Conclusion



- Cyber threat hunting cast as graph pattern matching.
- Efficient alignment algorithm for embedding threat behavior graph in kernel audit records provenance graph.
- Tested on real-world cyber attacks, ten red-team attack scenarios across three OS platforms.
- All attacks detected confidently, no false signals, and completed within minutes.

Acknowledgments



- [packetlabs] 239 Cybersecurity Statistics (2023) [<u>https://www.packetlabs.net/</u> posts/239-cybersecurity-statistics-2023/]
- [Prographer] PROGRAPHER: An Anomaly Detection System based on Provenance Graph Embedding, F. Yang, J. Xu, C. Xiong, Z. Li, K. Zhang, Usenix Sexurity 2023.
- [Holmes] HOLMES: Real-Time APT Detection through Correlation of Suspicious Information Flows, S. Momeni Milajerdi, R. Gjomemo, B. Eshete, R. Sekar, V. N. Venkatakrishnan, IEEE Symposium on Security and Privacy 2019.
- [Poirot] Poirot: Aligning Attack Behavior with Kernel Audit Records for Cyber Threat Hunting, S. M. Milajerdi, R. Gjomemo, B. Eshete, V.N. Venkatakrishnan, CCS, 2019.