A Series of Fortunate Events:

Attacker behavior analysis from observable sequences

Azqa Nadeem

PhD candidate

Cyber Analytics Lab

TU Delft

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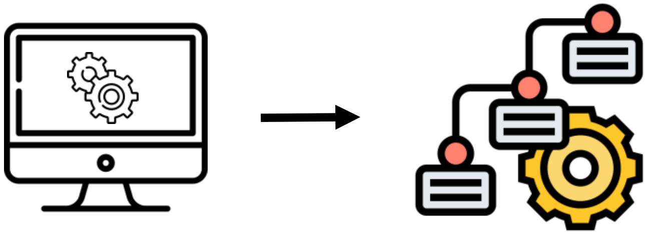
Cyber Analytics Lab

Dynamic observables

- Program execution → observable data
- Network traffic, software logs, intrusion alerts



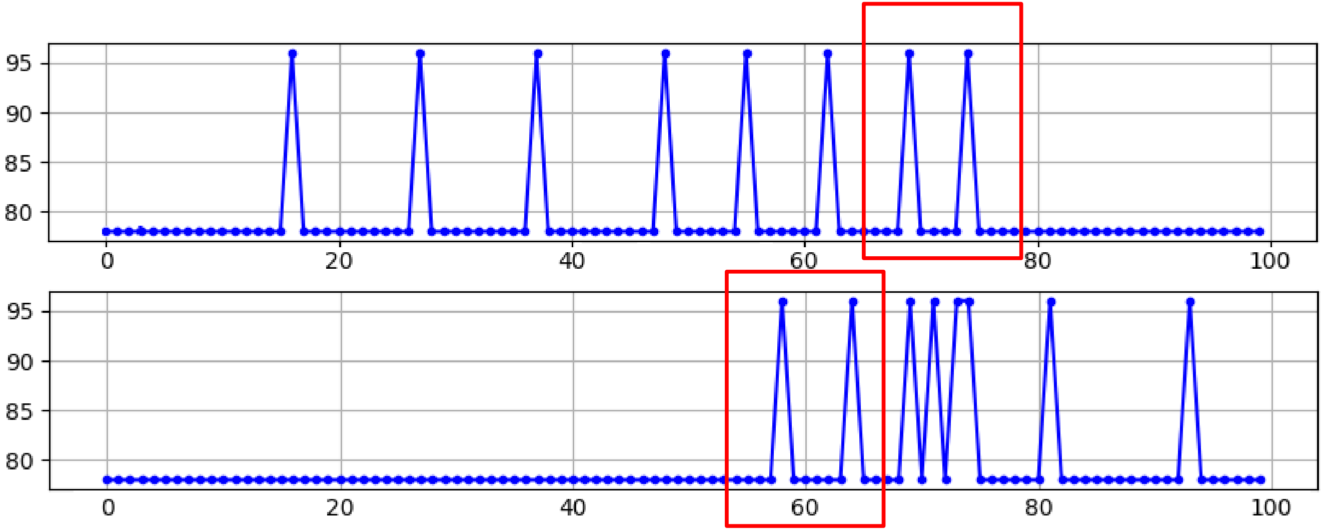
Dynamic observables

- Program execution → observable data
- Network traffic, software logs, intrusion alerts

- Proxy to attacker intent

Series of fortunate events → Sequences

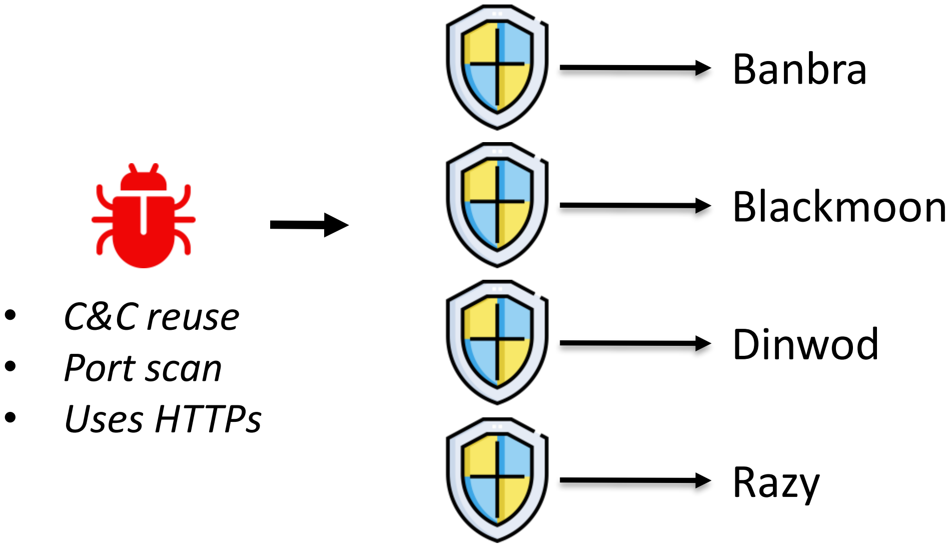
- Patterns in temporal data
- Limited data → insightful patterns
- Privacy non-invasive



Use cases

Case 1: Malware Behavior Profiles

- Malware labels are inconsistent and black-box



- *C&C reuse*
- *Port scan*
- *Uses HTTPs*

Banbra

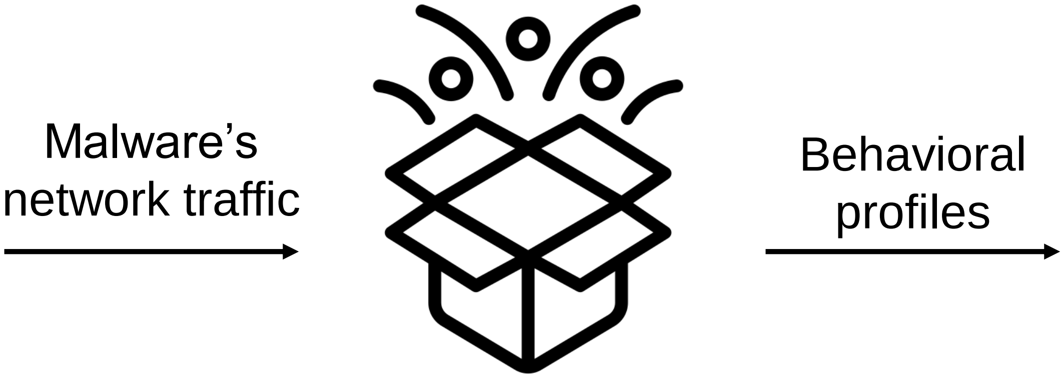
Blackmoon

Dinwod

Razy

Case 1: Malware Behavior Profiles

- Malware labels are inconsistent and black-box
- How to discover behaviors?



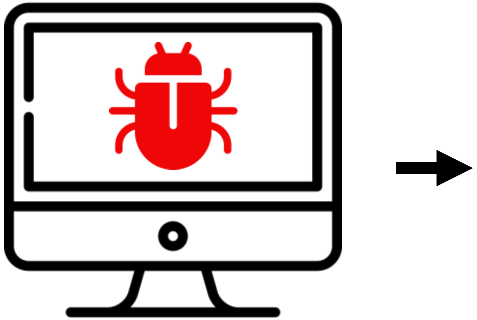
Malware's network traffic

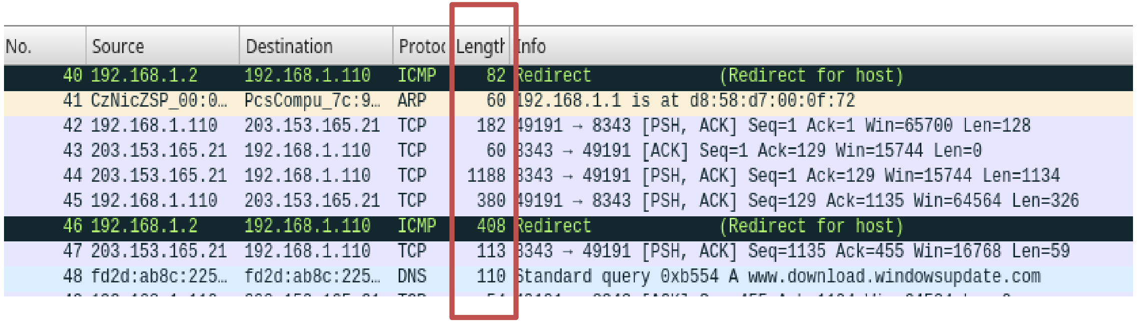
Behavioral profiles

MalPaCA

Case 1: Malware Behavior Profiles

- Malware infected machine generates network traffic





No.	Source	Destination	Protoc	Length	Info
40	192.168.1.2	192.168.1.110	ICMP	82	Redirect (Redirect for host)
41	CzNicZSP_00:0…	PcsCompu_7c:9…	ARP	60	192.168.1.1 is at d8:58:d7:00:0f:72
42	192.168.1.110	203.153.165.21	TCP	182	49191 → 8343 [PSH, ACK] Seq=1 Ack=1 Win=65700 Len=128
43	203.153.165.21	192.168.1.110	TCP	60	8343 → 49191 [ACK] Seq=1 Ack=129 Win=15744 Len=0
44	203.153.165.21	192.168.1.110	TCP	1188	8343 → 49191 [PSH, ACK] Seq=1 Ack=129 Win=15744 Len=1134
45	192.168.1.110	203.153.165.21	TCP	380	49191 → 8343 [PSH, ACK] Seq=129 Ack=1135 Win=64564 Len=326
46	192.168.1.2	192.168.1.110	ICMP	408	Redirect (Redirect for host)
47	203.153.165.21	192.168.1.110	TCP	113	8343 → 49191 [PSH, ACK] Seq=1135 Ack=455 Win=16768 Len=59
48	fd2d:ab8c:225…	fd2d:ab8c:225…	DNS	110	Standard query 0xb554 A www.download.windowsupdate.com

Beyond Labeling: Using Clustering to Build Network Behavioral Profiles of Malware Families. *Azqa Nadeem, Christian Hammerschmidt, Carlos H. Ganan, Sicco Verwer. In Malware Analysis using Artificial Intelligence and Deep Learning, Springer, 2020. (Forthcoming)*

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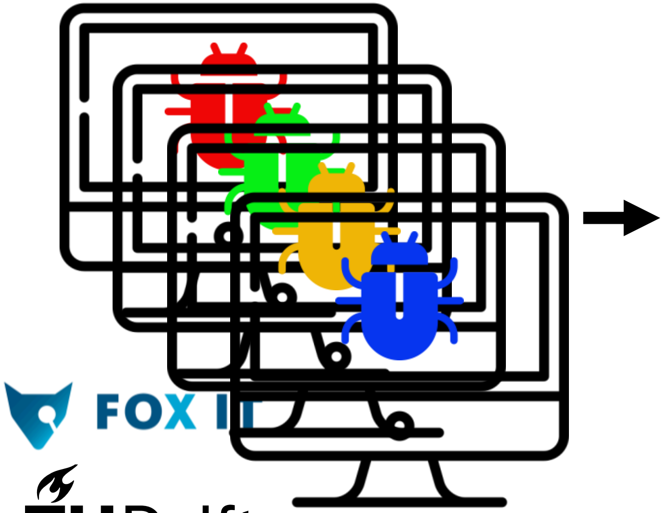

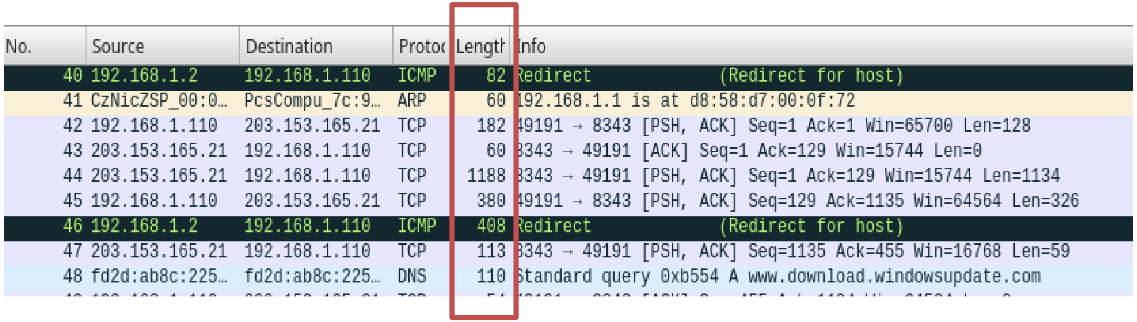

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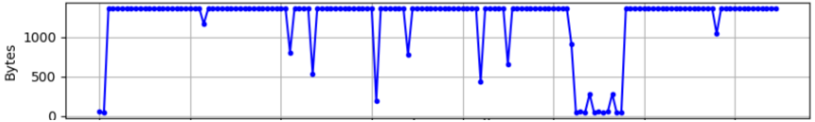
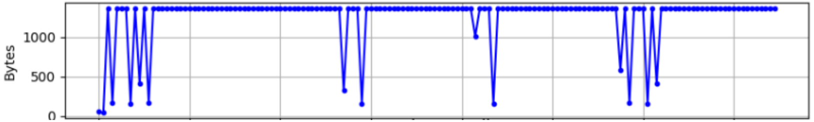
Case 1: Malware Behavior Profiles

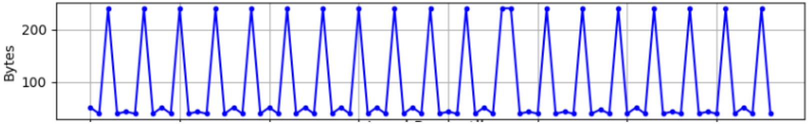
Zeus-738f →



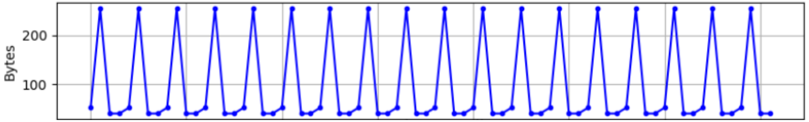
Gozi-4bd7 →



Zeus-78de →



Zeus-6631 →



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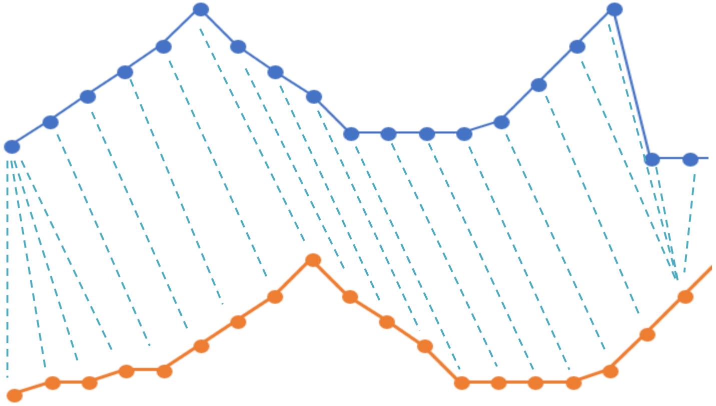

Dynamic Time Warping

$$D(i,j) = \left|A_i - B_j\right| + \min(D(i-1,j), D(i,j-1), D(i-1,j-1))$$

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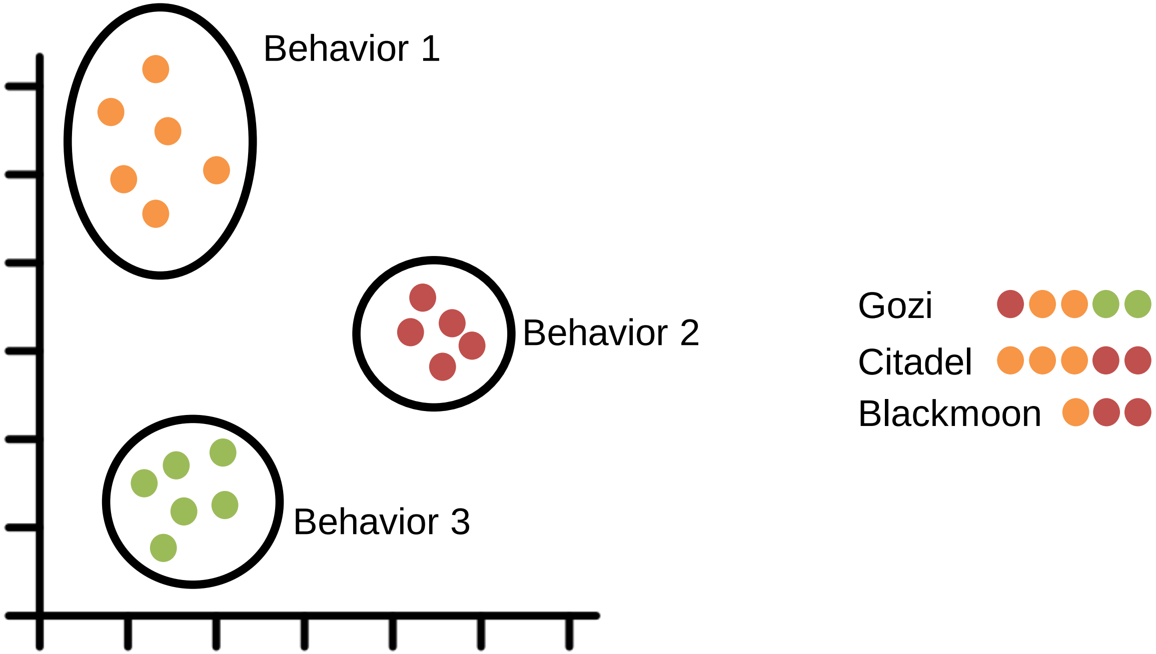

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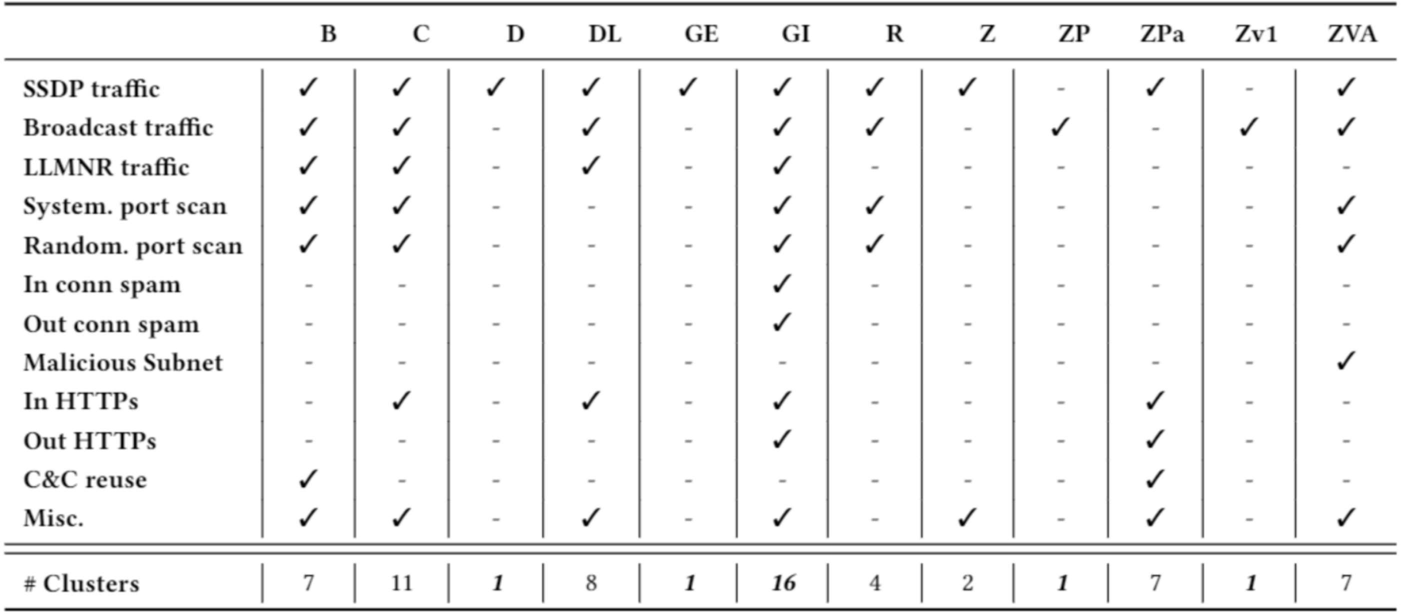

	B	C	D	DL	GE	GI	R	Z	ZP	ZPa	Zv1	ZVA
SSDP traffic	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	-	✓
Broadcast traffic	✓	✓	-	✓	-	✓	✓	-	✓	-	✓	✓
LLMNR traffic	✓	✓	-	✓	-	✓	-	-	-	-	-	-
System. port scan	✓	✓	-	-	-	✓	✓	-	-	-	-	✓
Random. port scan	✓	✓	-	-	-	✓	✓	-	-	-	-	✓
In conn spam	-	-	-	-	-	✓	-	-	-	-	-	-
Out conn spam	-	-	-	-	-	✓	-	-	-	-	-	-
Malicious Subnet	-	-	-	-	-	-	-	-	-	-	-	✓
In HTTPs	-	✓	-	✓	-	✓	-	-	-	✓	-	-
Out HTTPs	-	-	-	-	-	✓	-	-	-	✓	-	-
C&C reuse	✓	-	-	-	-	-	-	-	-	✓	-	-
Misc.	✓	✓	-	✓	-	✓	-	✓	-	✓	-	✓
# Clusters	7	11	***1***	8	***1***	***16***	4	2	***1***	7	***1***	7

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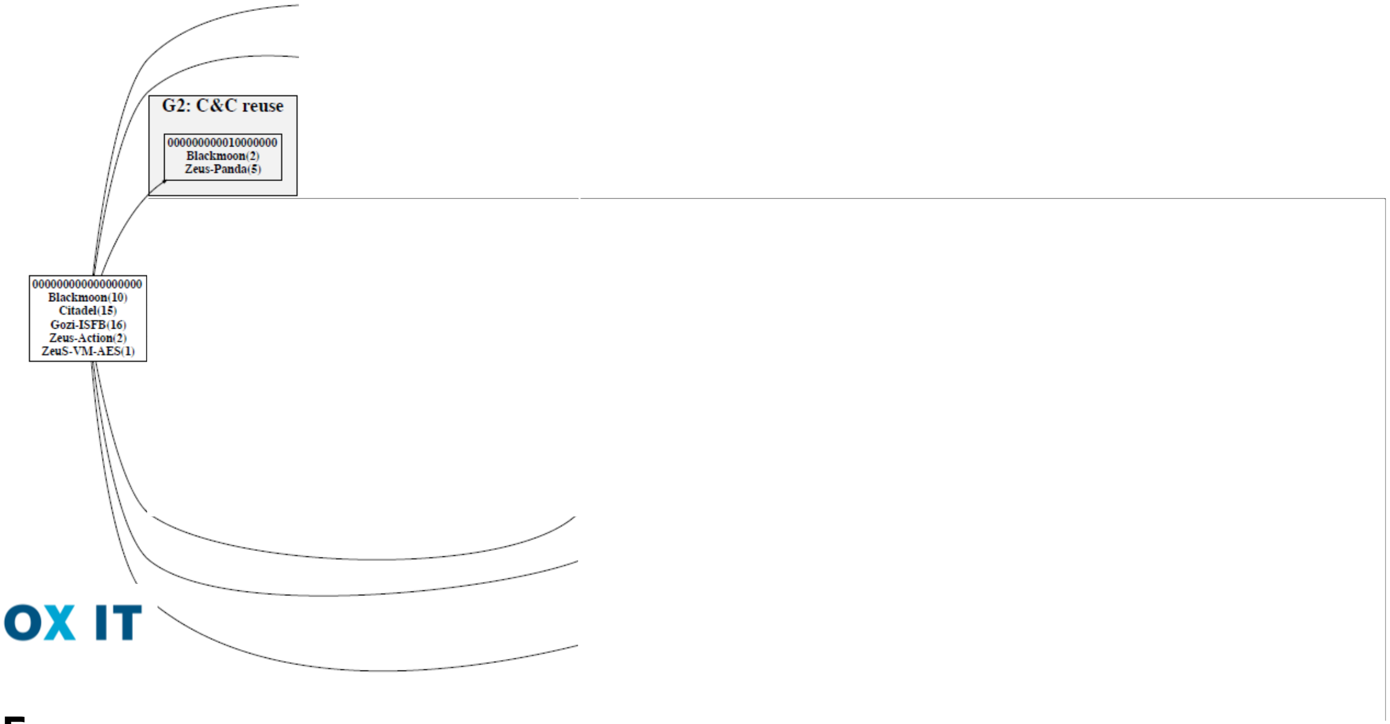

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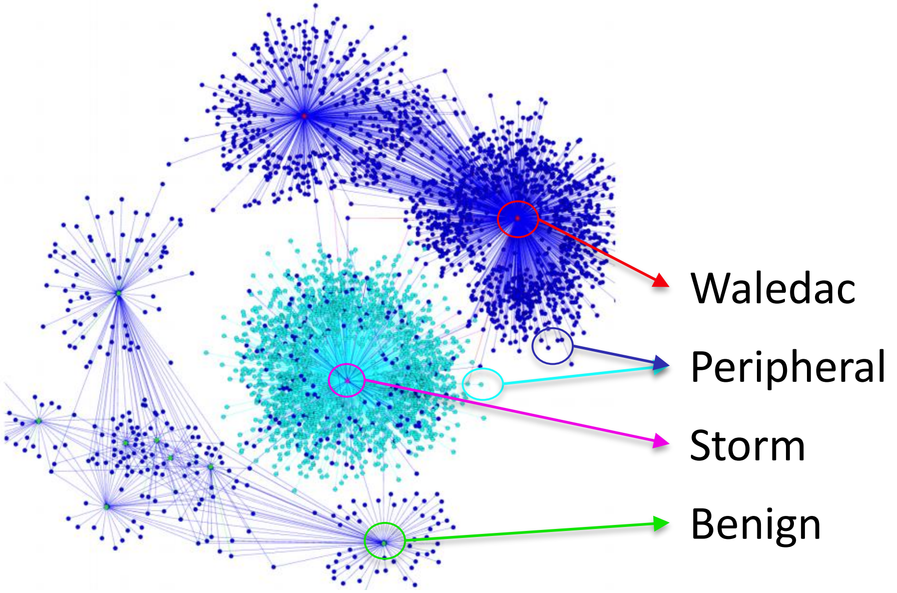
Case 1 (ext.): Detecting network communities

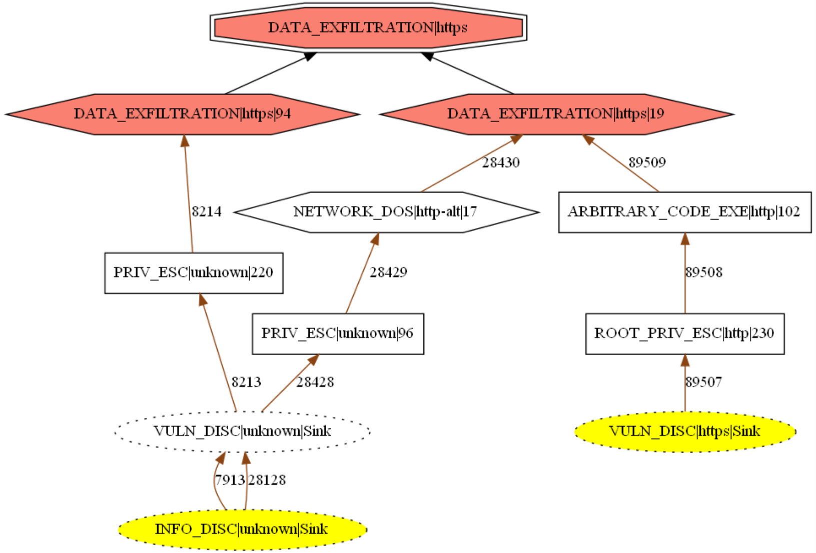
- What type of hosts are present in a network?
  - Connection + Host clustering



Hybrid Connection and Host Clustering for Community Detection in Spatial-temporal Network Data. Mark Patrick Roeling, Azqa Nadeem, Sicco Verwer. In Machine Learning for Cybersecurity (MLCS), 2020

Case 2: Attacker strategy analysis

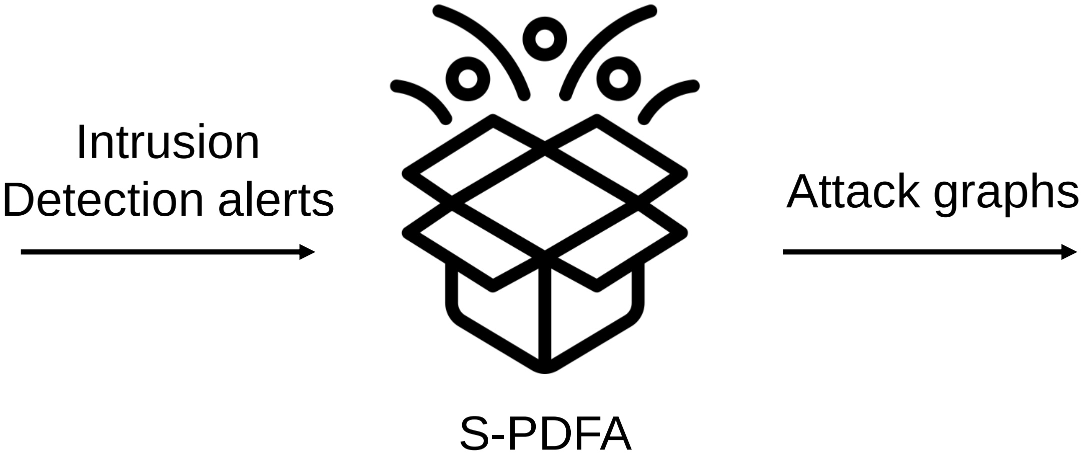
- Alert correlation groups related alerts
  - But how did the attack happen?
- How to get attacker strategies automatically?



Ideally…

- *From intrusion alerts*
- *Without expert knowledge*

Case 2: Attacker strategy analysis

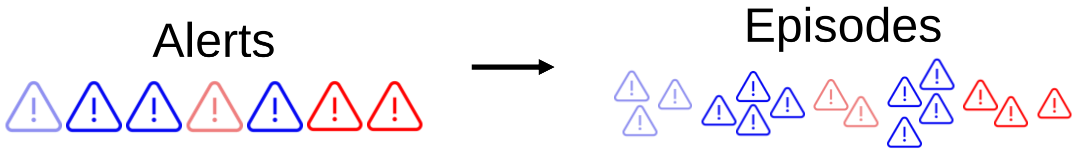


Intrusion Detection alerts

Attack graphs

S-PDFA

Case 2: Attacker strategy analysis



Alerts

Episodes

Alert-driven attack graphs using S-PDFA. Azqa Nadeem, Sicco Verwer, Stephen Moskal, Shanchieh Jay Yang. In IEEE Transactions on Dependable and Secure Computing, 2021. (Submitted)

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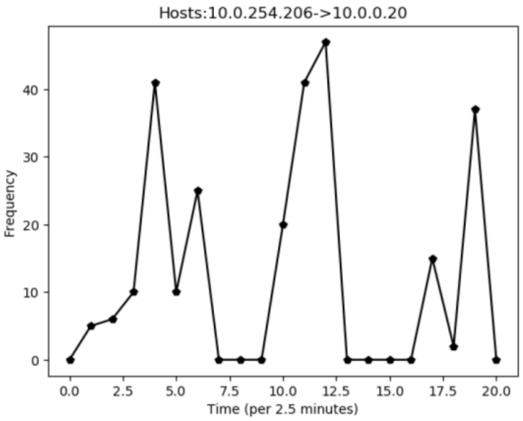
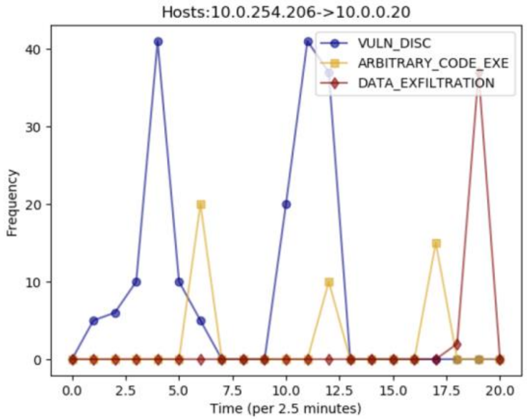
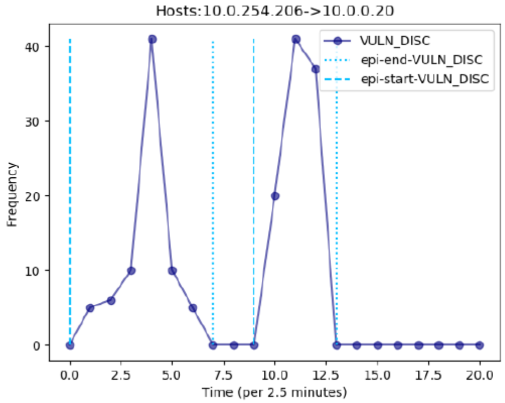
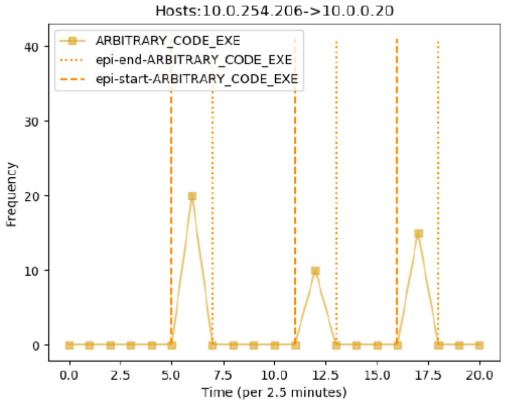
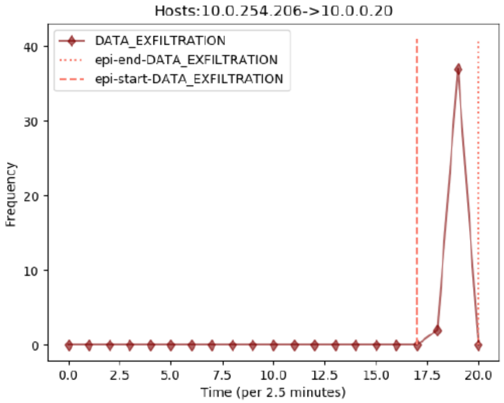




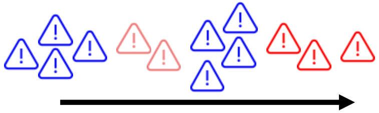


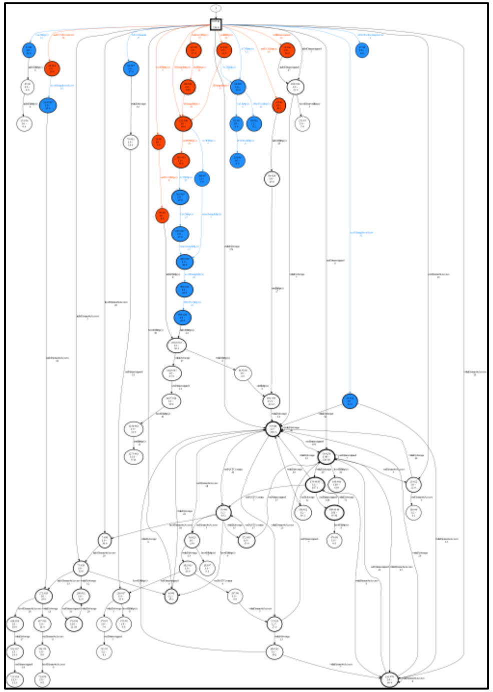




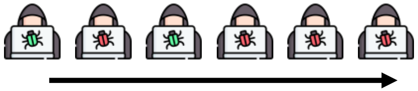
Case 2: Attacker strategy analysis

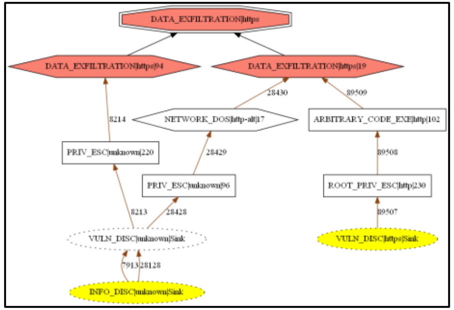
Episodes





Actions

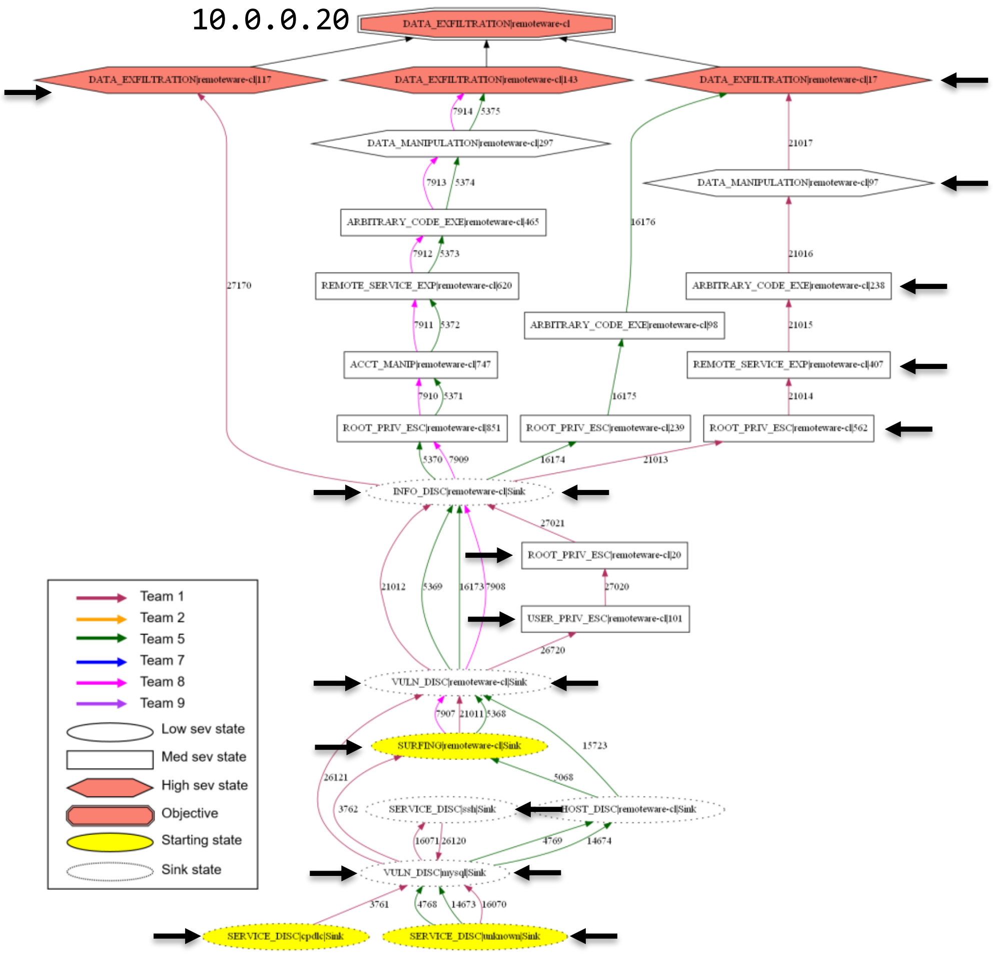




Alert-driven attack graphs using S-PDFA. Azqa Nadeem, Sicco Verwer, Stephen Moskal, Shanchieh Jay Yang. In IEEE Transactions on Dependable and Secure Computing, 2021. (Submitted)

Insights

- Attackers follow shorter paths after discovering longer ones


10.0.0.20
DATA_EXFILTRATION|remoteware-cl
DATA_EXFILTRATION|remoteware-cl|117
DATA_EXFILTRATION|remoteware-cl|143
DATA_EXFILTRATION|remoteware-cl|17
7914
5375
DATA_MANIPULATION|remoteware-cl|297
21017
DATA_MANIPULATION|remoteware-cl|97
7913
5374
ARBITRARY_CODE_EXE|remoteware-cl|465
16176
21016
7912
5373
27170
REMOTE_SERVICE_EXP|remoteware-cl|620
ARBITRARY_CODE_EXE|remoteware-cl|238
ARBITRARY_CODE_EXE|remoteware-cl|98
7911
5372
21015
ACCT_MANIP|remoteware-cl|747
REMOTE_SERVICE_EXP|remoteware-cl|407
7910
5371
16175
21014
ROOT_PRIV_ESC|remoteware-cl|851
ROOT_PRIV_ESC|remoteware-cl|239
ROOT_PRIV_ESC|remoteware-cl|562
5370
7909
16174
21013
INFO_DISC|remoteware-cl|Sink
27021
ROOT_PRIV_ESC|remoteware-cl|20
21012
5369
16173
7908
27020
USER_PRIV_ESC|remoteware-cl|101
26720
VULN_DISC|remoteware-cl|Sink
7907
21011
5368
SURFING|remoteware-cl|Sink
15723
26121
5068
3762
SERVICE_DISC|ssh|Sink
HOST_DISC|remoteware-cl|Sink
16071
26120
4769
14674
VULN_DISC|mysql|Sink
3761
4768
14673
16070
SERVICE_DISC|cpdlc|Sink
SERVICE_DISC|unknown|Sink
Team 1
Team 2
Team 5
Team 7
Team 8
Team 9
Low sev state
Med sev state
High sev state
Objective
Starting state
Sink state

CyberVSR RIT

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Future research directions

- Additional use cases for sequential ML
- Defining explainability in security
- Running qualitative studies with analysts

Wrap-up

- Sequence of dynamic observables → attacker intent
- Input: observables | Output: Intelligence

- Unsupervised setting with limited expert knowledge

- 2 use-cases
  - Network traffic → Malware behavior profiles
  - Intrusion alerts → Attacker strategy attack graphs

Thank you!
Questions?

Sequence of dynamic observables → attacker intent

Input: observables | Output: Intelligence

Unsupervised setting with limited expert knowledge

2 use-cases

- Network traffic → Malware behavior profiles
- Intrusion alerts → Attacker strategy attack graphs

azqa.nadeem@tudelft.nl https://cyber-analytics.nl/

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