THE GEORGE WASHINGTON UNIVERSITY

WASHINGTON, DC

Detecting Lateral Movement in Enterprise Computer Networks with Unsupervised Graph AI

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Graph Lab

Overview

1. Lateral Movement & The Lifecycle of a Cyber Attack
2. Machine Learning on Graphs & Unsupervised Graph AI
3. Detecting Lateral Movement with Unsupervised Graph AI
4. Evaluations and Results
5. Conclusion

Overview

1 **Lateral Movement & The Lifecycle of a Cyber Attack**

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Lifecycle of a Cyber Attack

- Advanced Persistent Threats (APTs) are stealthy and sophisticated threat actors

- Attacks waged by APTs are complex, multi-stage campaigns that can span long periods of time

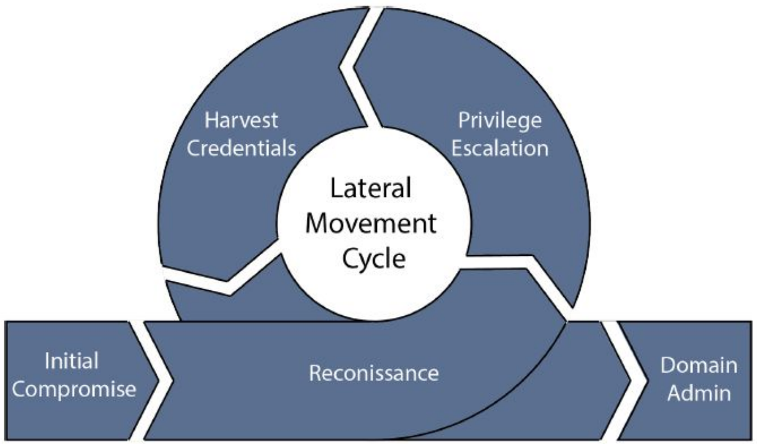


Figure 2: An APT-style campaign showing the cycle of lateral movement after initial compromise and prior to full domain ownership.

Lifecycle of a Cyber Attack

- Initial compromise typically occurs on low-privilege systems as these users are typically more susceptible to low-level attacks
    - Phishing
    - Credential stuffing
    - Bad passwords

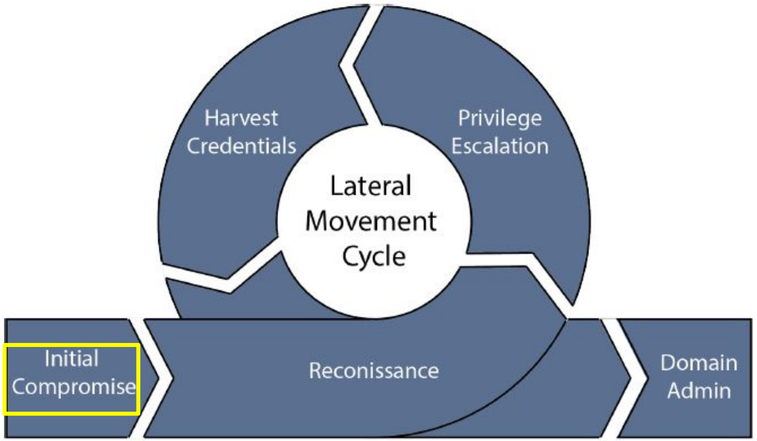
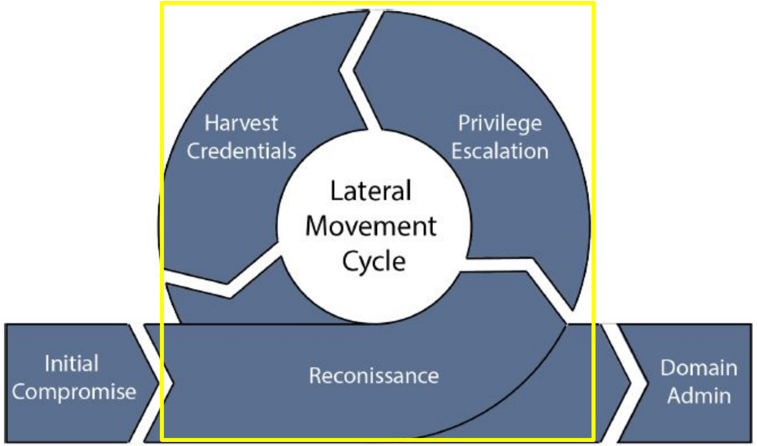


Figure 2: An APT-style campaign showing the cycle of lateral movement after initial compromise and prior to full domain ownership.

Lifecycle of a Cyber Attack

- The adversary then must move laterally through the network to gain access to systems necessary to accomplish their mission
  - Reconnaissance to identify accessible systems and services
  - Privilege escalation either on the local machine or by moving to a machine where the user has more privileges
  - Credential harvesting from memory or files



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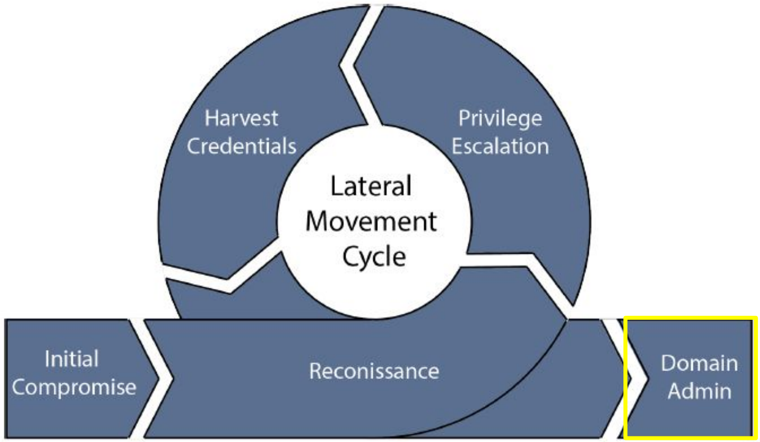
Lifecycle of a Cyber Attack

- The last phase are the actual actions on objectives
  - Domain Admin
  - Data Exfiltration
  - Data Destruction
  - Ransomware



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Lateral Movement

- Key stage of the attack lifecycle that allows the adversary to achieve their actions on objectives

- Challenging to detect as often adversaries will use *legitimate credentials, services, and authentication channels*
  - WMI, WinRM, RDP, SMB, etc

We need a technique capable of learning from past authentication behavior, that will allow us to detect anomalous authentication events that may be indicative of lateral movement.

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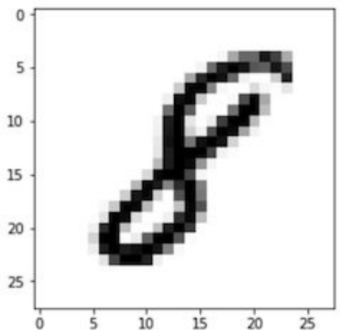
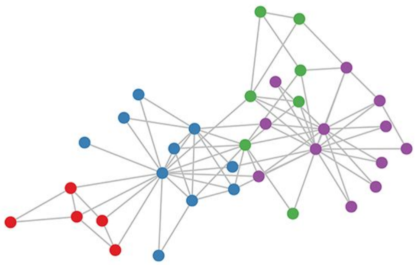
Machine Learning on Graphs

- Graph data structures consisting of a set of nodes and edges are extremely powerful for representing heterogeneous relational data (social networks, computer networks, knowledge graphs, etc)

- Applying ML to graphs is non-trivial due to non-euclidian nature of the data





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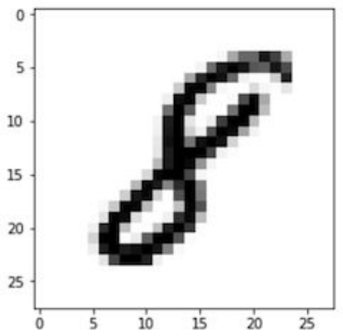
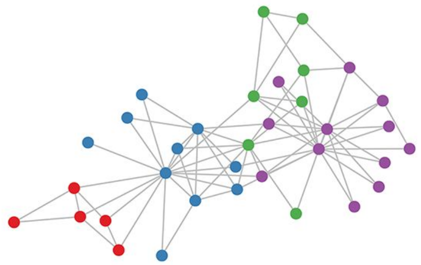
Location & order
is meaningful!





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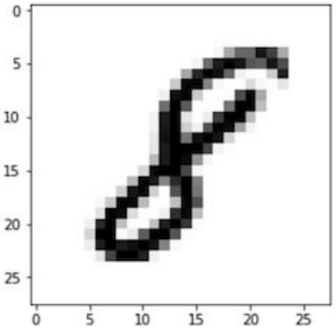
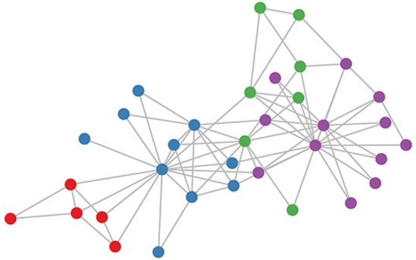
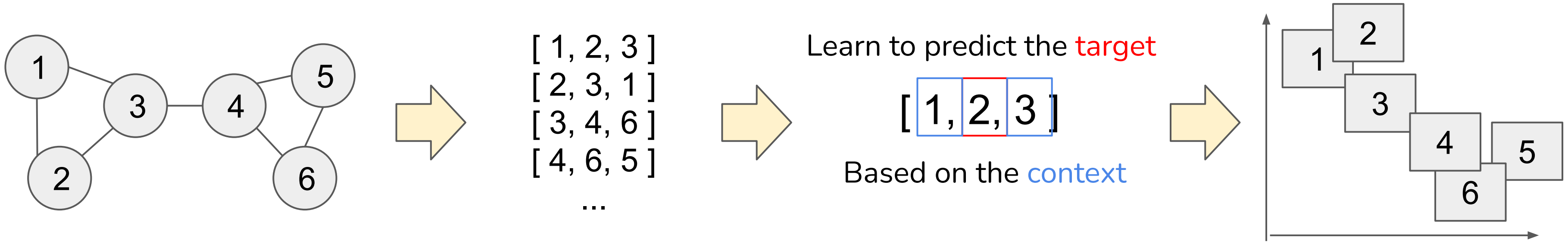




No location!
No order!

Unsupervised Graph AI

- Graphs can be sampled to form fixed-length sequences of nodes which can be used in conjunction with traditional data mining techniques from NLP (popularized by works such as DeepWalk and node2vec)



Input Graph **Random Walk Sampling** **CBOW Embedding** **Tuned Embeddings**

Grover, Aditya, and Jure Leskovec. "node2vec: Scalable feature learning for networks." *SIGKDD* 2016.
Perozzi, Bryan, Rami Al-Rfou, and Steven Skiena. "Deepwalk: Online learning of social representations." *SIGKDD* 2014.

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Method

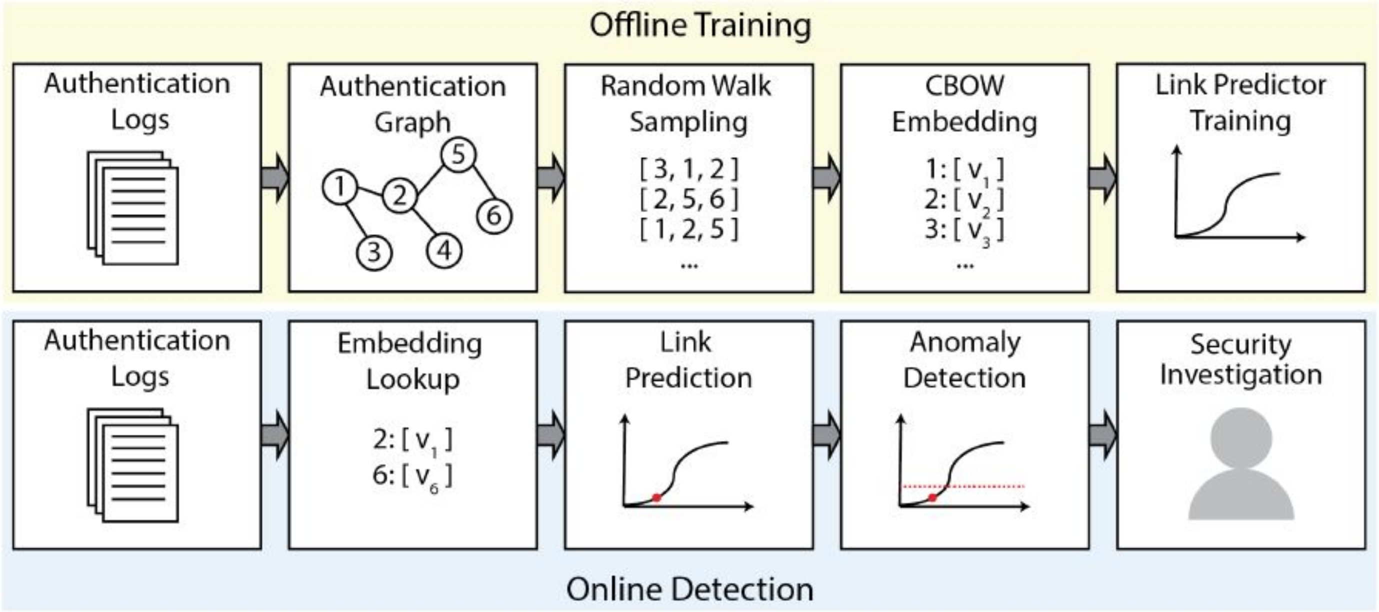
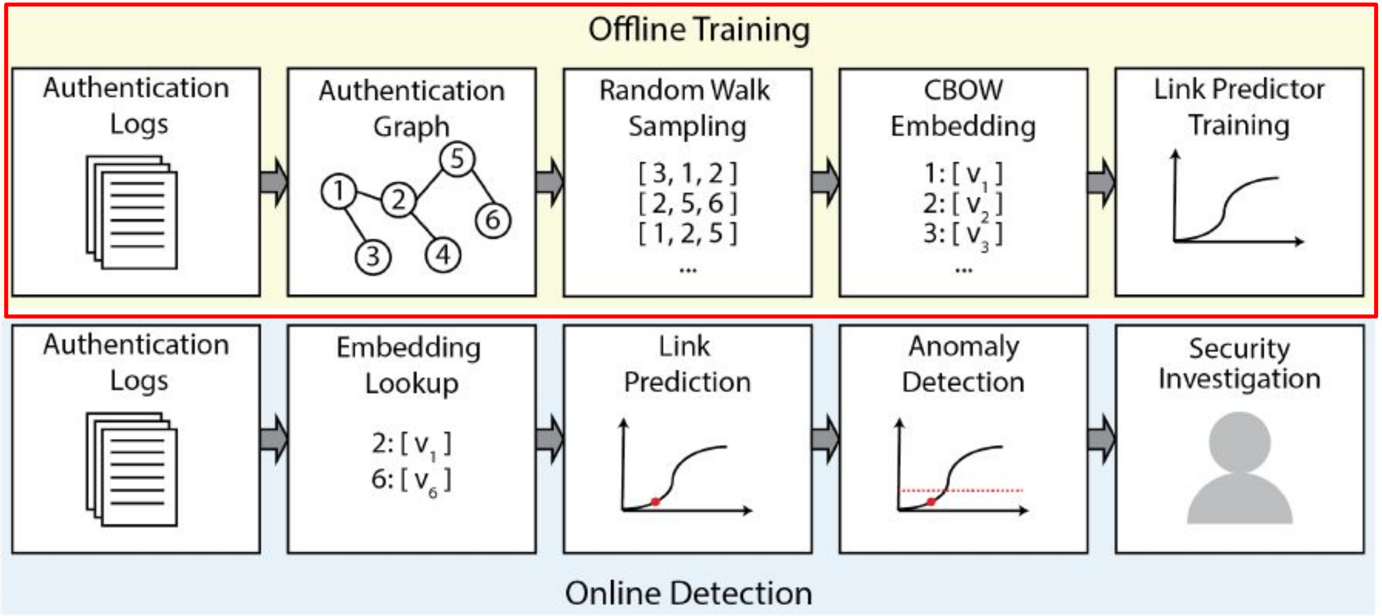


Figure 3: Full algorithm pipeline including offline training of node embeddings and logistic regression link predictor, as well as online detection via an embedding lookup, link prediction, and threshold-based anomaly detection.

Method



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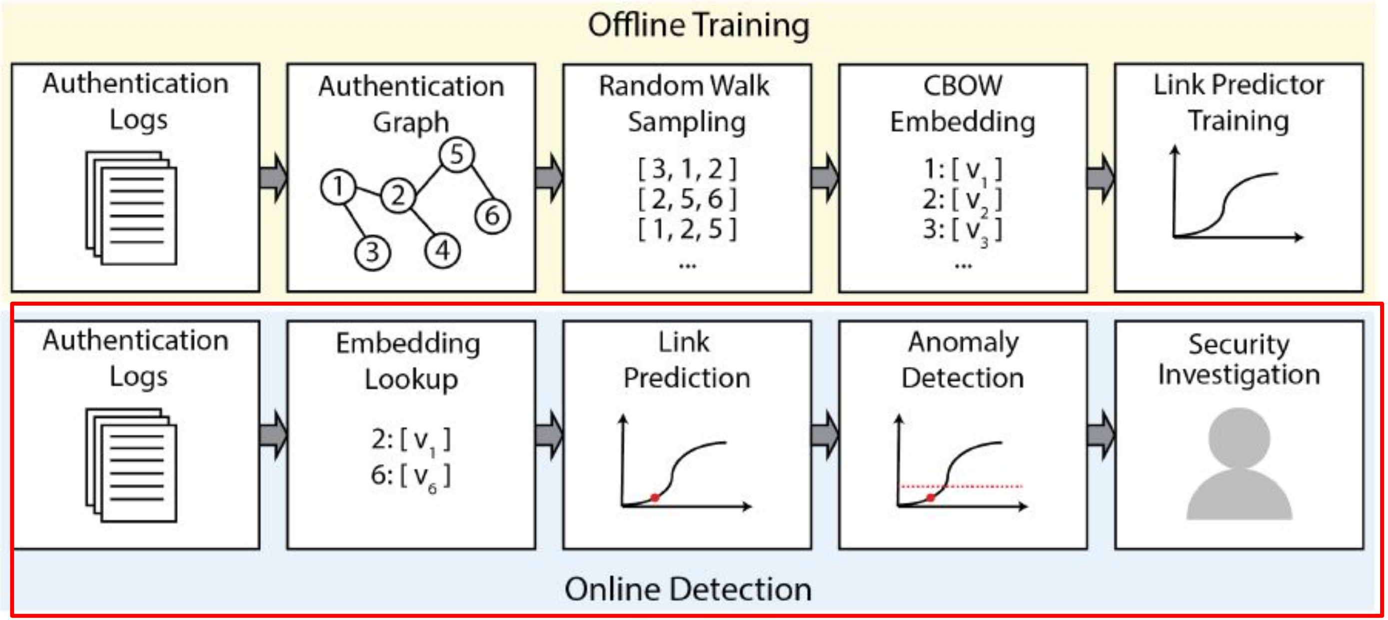


Figure 3: Full algorithm pipeline including offline training of node embeddings and logistic regression link predictor, as well as online detection via an embedding lookup, link prediction, and threshold-based anomaly detection.

Authentication Graph Generation

- Parse industry standard Kerberos logs to build an Authentication Graph
- Kerberos is a network authentication protocol - does not require host logs
- Extracted fields:
  - Client & Service Principals
  - IP Addresses
- “Who is authenticating to what, from where”

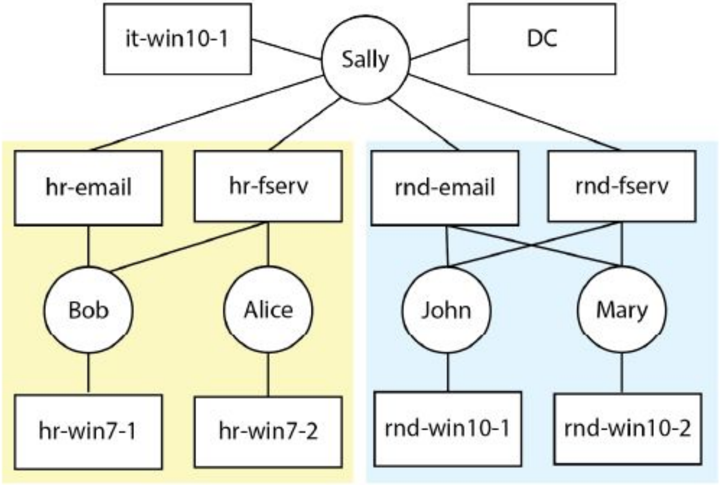


Figure 1: Example of an authentication graph for a small simulated network.

Node Embedding

- Embedding process based on node2vec
- Random walks generate sequences of nodes
- CBOW is used to learn node embeddings

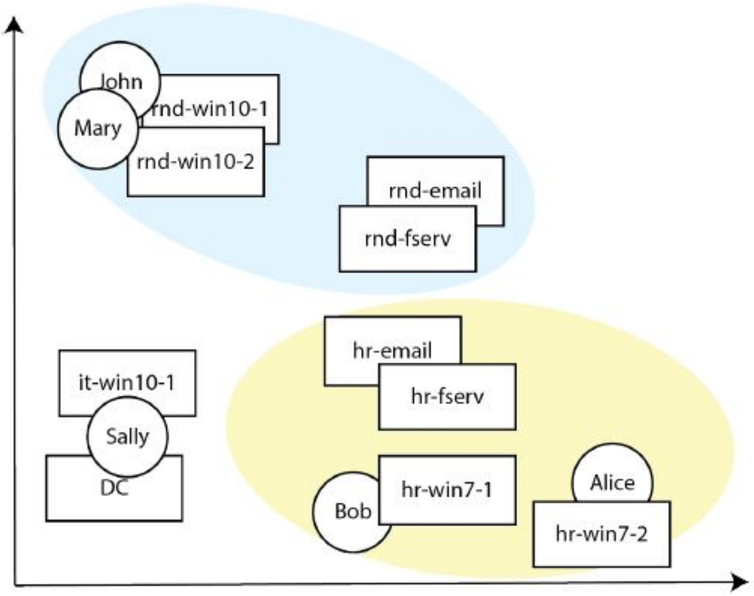
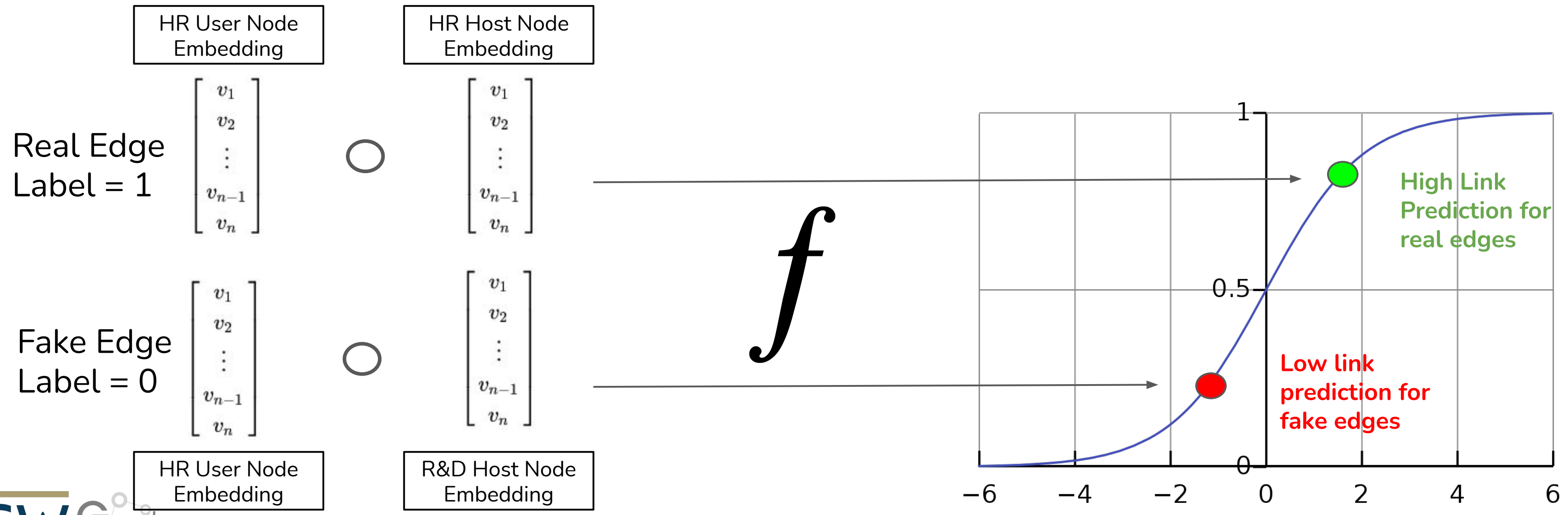


Figure 4: Example embedding space generated from a random-walk based node-embedding process.

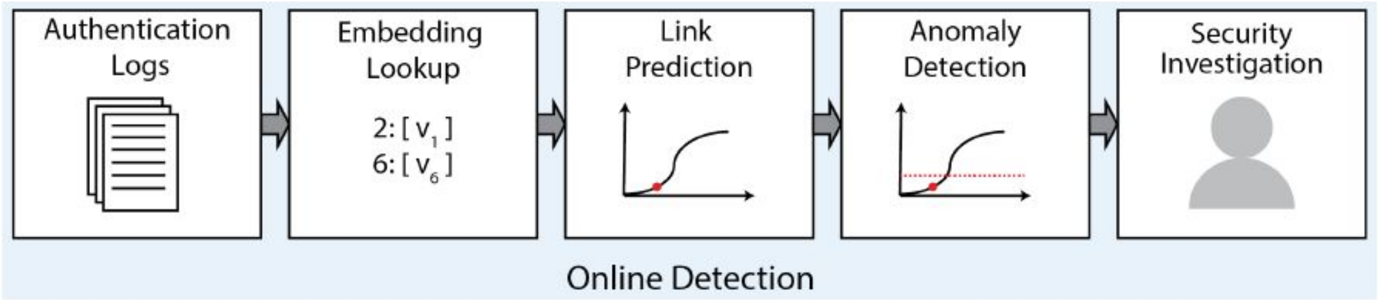
Grover, Aditya, and Jure Leskovec. "node2vec: Scalable feature learning for networks." *SIGKDD* 2016.

Link Predictor

- A logistic regression classifier is trained on node embeddings from real & fake edges in the graph



Detection



- Anomalous link detection can be achieved by alerting on links with a probability less than a user-defined threshold $\boldsymbol{\delta}$

$$A(h_a, h_b) = \begin{cases} 1, & if\ f(h_a \circ h_b) < \delta \\ 0, & otherwise \end{cases}$$

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Datasets

- PicoDomain Dataset
  - Custom dataset we built in-house https://github.com/iHeartGraph/PicoDomain
  - Characterized by its small size, but full visibility into a cyber attack that spans the killchain
- LANL 2015 Dataset
  - Real-world, enterprise network from
  - Characterized by its large size, but highly anonymized data, with very little detail on malicious activity

Table 1: Dataset Details

	PicoDomain	LANL
Duration in Days	3	58
Days with Attacks	2	18
Total Records	4686	1.05 B
Total Attack Records	129	749
User and Machine Accounts	86	99968
Computers	6	17666

Comparison Techniques

Graph ML

Graph-Learning **Local-View** (GLGV): **small** node embedding context window

Graph-Learning **Global-View** (GLGV): **large** node embedding context window

Traditional ML: 1-hot encoded authentication feature vector per-entity

Local Outlier Factor (LOF) - local density-based outliers

Isolation Forest (IF) - decision-tree-based anomaly detector

Rule-Based

Unknown Authentication (UA) - alert on authentications not previously observed

Failed Authentication (FA) - alert on failed authentication attempts

Results on PicoDomain

- UA detects the most malicious activity
- ML detects some malicious events but FPR too high
- GL achieves 80% TPR at 0% FPR

Table 2: Anomaly Detection Results on PicoDomain Dataset

Algorithm	**TP**	**FP**	**TPR (%)**	**FPR (%)**
UA	**129**	11	**100**	1.5
FL	1	15	0.8	2.0
LOF	41	19	32	2.5
IF	34	62	26	8.3
GL-LV	102	**0**	80	**0.0**
GL-GV	102	**0**	80	**0.0**

Results on LANL Dataset

- UA still detects most of malicious activity but at expense of FPs
- ML techniques are noisy and don't detect much activity
- GL-GV has best TPR and least FPR

Table 3: Anomaly Detection Results on LANL Dataset

Algorithm	TP	FP	TPR (%)	FPR (%)
UA	542	530082	72	4.4
FL	31	116600	4	1.0
LOF	87	169460	12	9.6
IF	65	299737	9	16.9
GL-LV	503	146285	67	1.2
GL-GV	**635**	**107960**	**85**	**0.9**

Reducing False Positives

- False positives are bad, waste time, and are a serious problem in cyber

- What can we learn from the data to help reduce the number of FPs?

Observation 1: The malicious authentication events are predominantly first authentication events.

Observation 2: The malicious authentication events are predominantly based on user interactions.

Observation 3: The malicious authentication events are predominantly related to a few specific user accounts and systems.

False Positive Filters

Figure 5: Impact of various approaches in reducing the number of false positives returned on the LANL dataset.

False Positive Filters

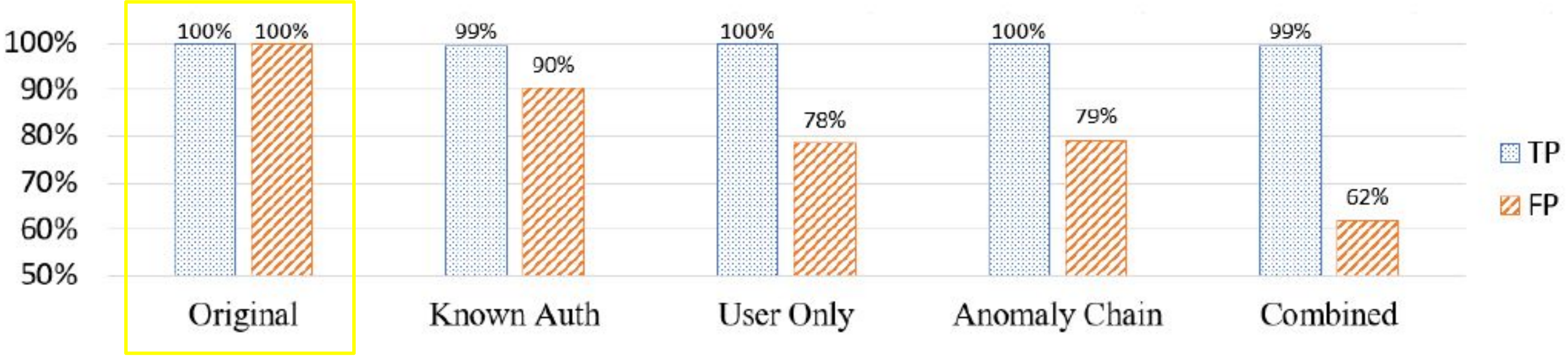

Figure 5: Impact of various approaches in reducing the number of false positives returned on the LANL dataset.

Original results on the LANL dataset presented previously

False Positive Filters

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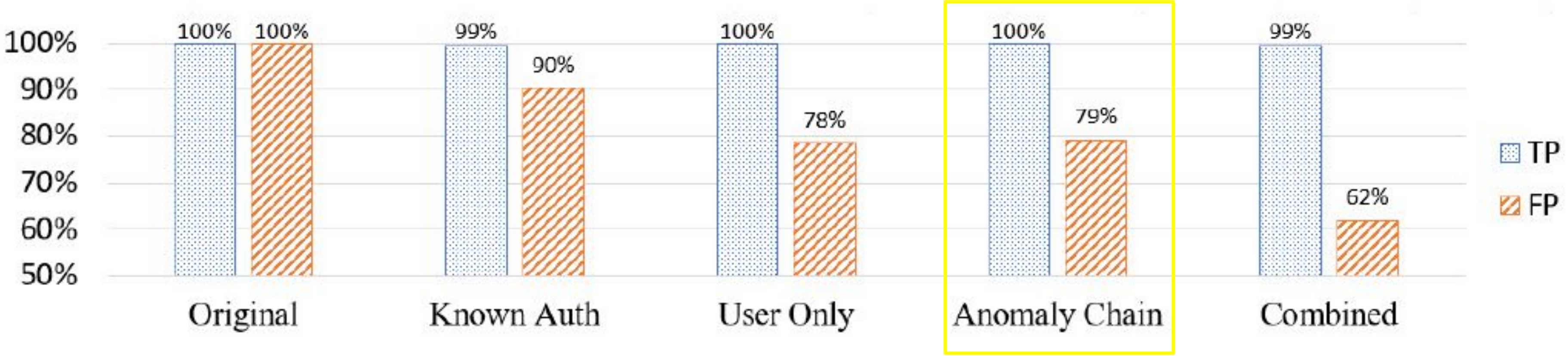
Filter out anomalies from authentications seen during training

False Positive Filters

Figure 5: Impact of various approaches in reducing the number of false positives returned on the LANL dataset.

Filter out anomalies that don’t involve a user account

False Positive Filters



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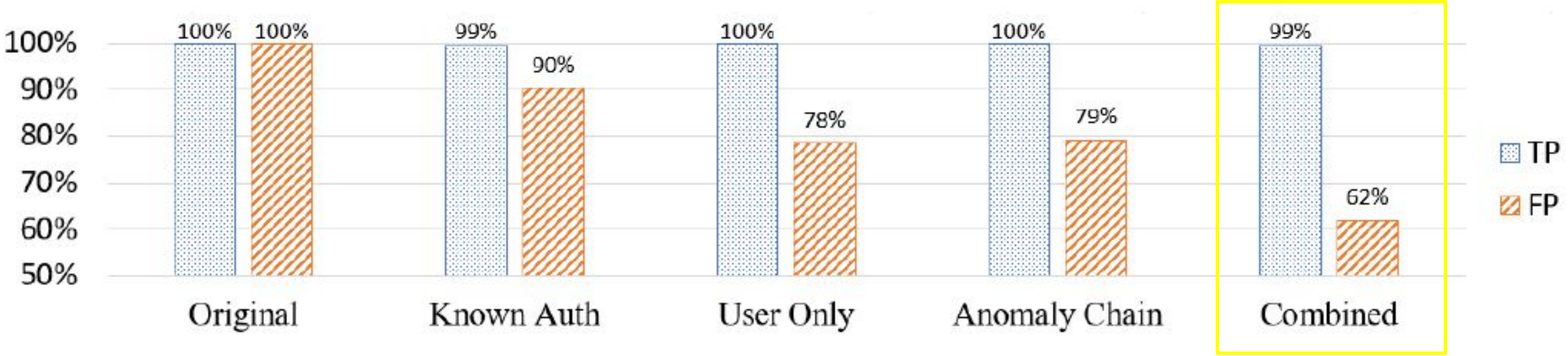
Filter out anomalies singletons

False Positive Filters



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Combining all filters together

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Conclusion

- Lateral movement is a critical phase of APT cyber attack campaigns that is very challenging to detect
- Using an authentication graph data structure, and unsupervised Graph AI, we can learn patterns of authentication activity of different classes of users
- We can use these learned patterns to detect malicious lateral movement with improved accuracy over several baseline detection algorithms
- With some simple post-processing filters we can reduce the number of false positives by nearly 40%.

Thanks!

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