ProcAID: Process Anomaly-based Intrusion Detection

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THE GEORGE WASHINGTON UNIVERSITY
WASHINGTON, DC

Agenda

- Motivation and Challenges
- Methodology
- Algorithm Comparison
- Results
- Future Work
- Implications and Conclusion

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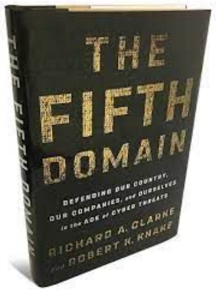
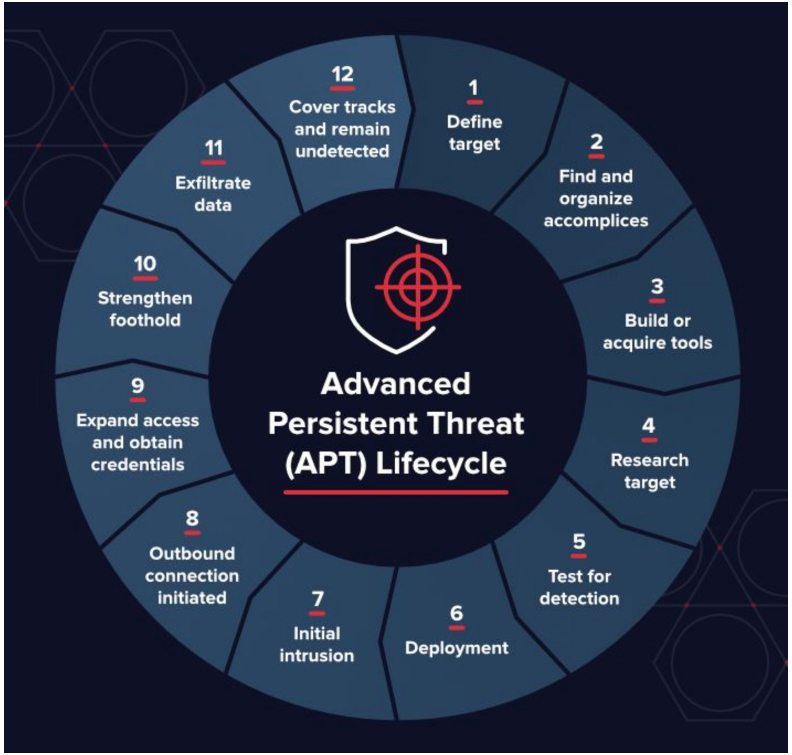
Motivation

- Advanced Persistent Threat (APT) success in current landscape
  - Nation-state actors
  - Well-funded and well-staffed
- APT targets:
  - Critical infrastructure, trade secrets, supply chains
- Offensive preference in computer science, cybersecurity, information technology and networking

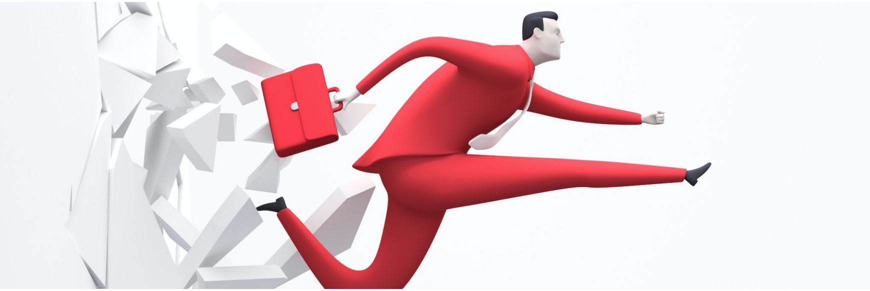




Challenges

- First intrusion detection model, invented by Dorothy Denning
  - Definition: any deviation in normal operations on a system
- State of intrusion detection
  - Signature-based
  - Anomaly-based
    - ProcAID
- APTs have breached the capabilities of current assets
  - Organization must employ multiple assets at the host and network level to effectively respond

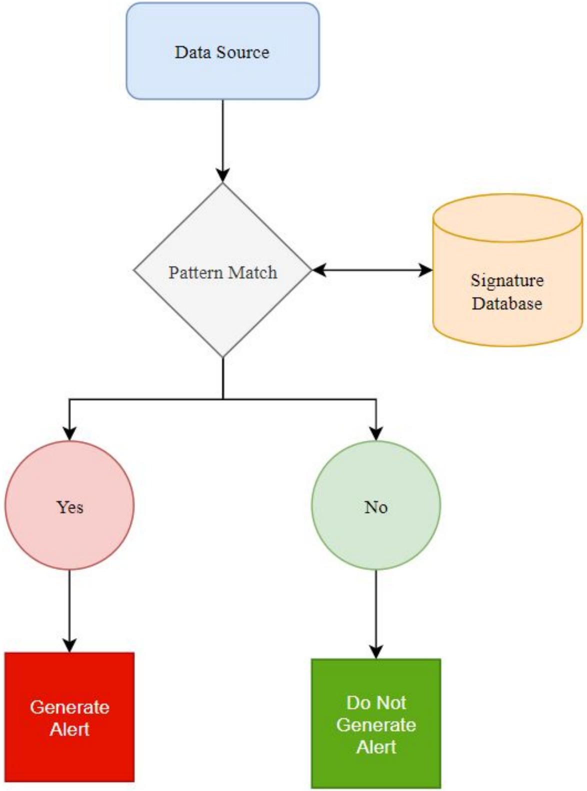
https://miro.medium.com/max/1024/1*dSn6e4V_cP-5Nm9LhACpLw.png



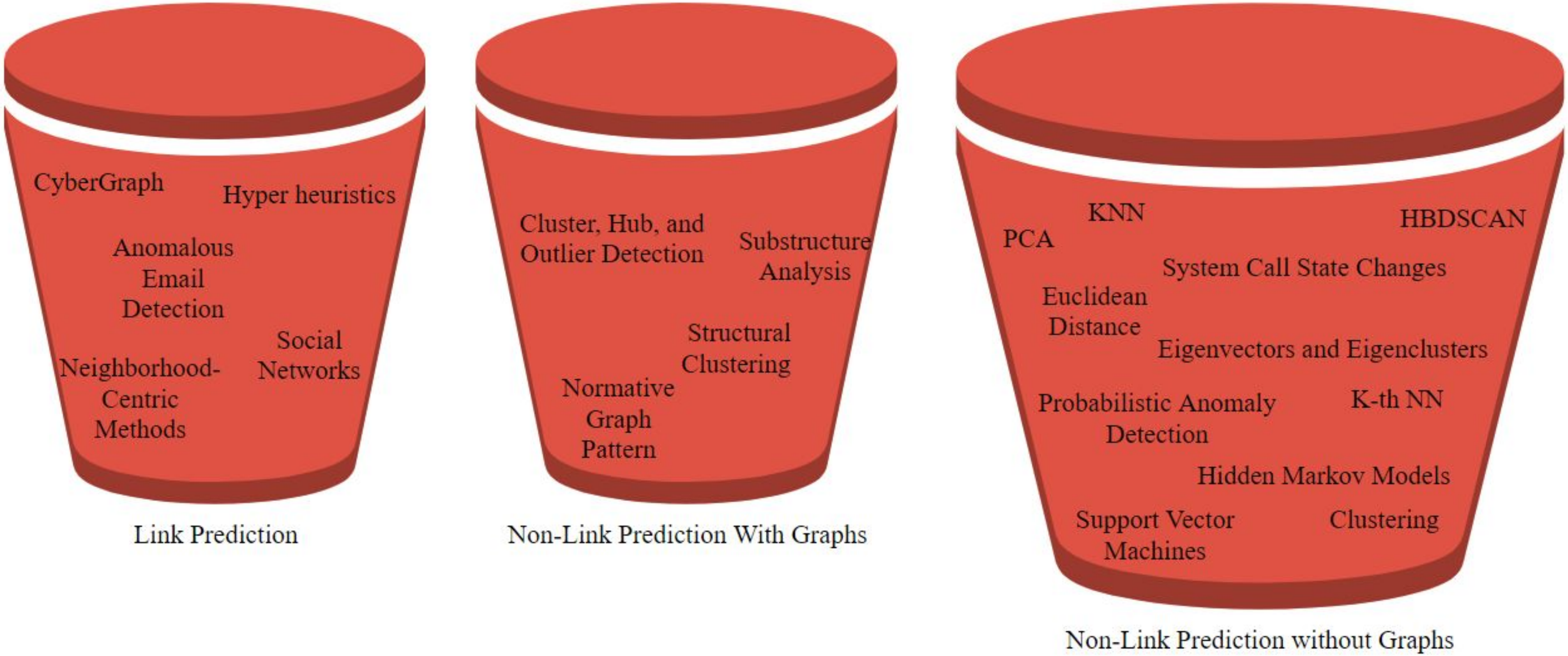
https://www.securityroundtable.org/breach-part-best-defense-good-offense/

Signature-based Detection Challenges

- Focus on pattern/signature matching in database
- Un-intelligent system
- Principal failure:
  - To detect unknown attacks
  - To detect patterns in behavior
- Common APT characteristics
  - “Live off the land”
  - Zero-Days
  - Blend-in with the environment
  - Intelligent exploitation



Prior Work in Anomaly Detection



Agenda

Motivation and Challenges

Methodology

Algorithm Comparison

Results

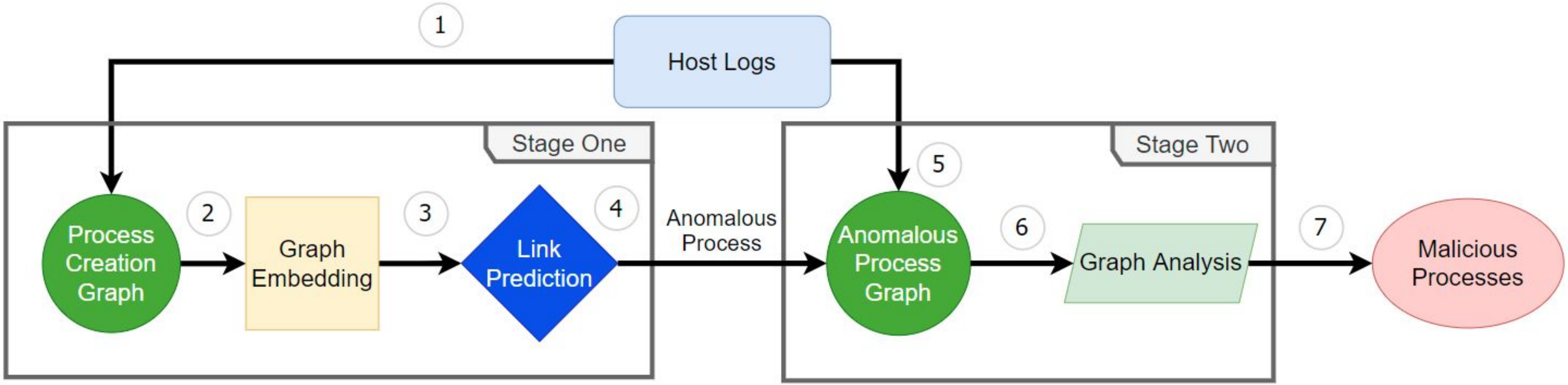
Future Work

Implications and Conclusion

ProcAID Methodology

Stage One: Unsupervised Anomaly Detection via Link Prediction

Stage Two: Inverse Graph Leadership and Inverse Graph Density Analysis



ProcAID Algorithm

- Ingests all host logs
- Returns anomalies with maliciousness scores
- Stage One
  - Lines 1-4
- Stage Two
  - Lines 6-20

Algorithm 1 ProcAID Algorithm

```
Input:  HostLogs
Output:  Anom,MalScore
 1: //Stage One
 2: ProcGraphTrain=CreateGraph(CreateProcTrain)
 3: ProcGraphTest=CreateGraph(CreateProcTest)
 4: ProcAnomalies=GraphAnomaly(ProcGraphTrain,ProcGraphTest,Thres)
 5: //Stage Two
 6: MalEdgeCollection=FindLogs(ProcAnomalies)
 7: for edge in MalEdgeCollection do
 8:   for parentproc in edge do
 9:     ParentProcData=SplitTime(parentproc,Time)
10:     EvaluationGraph=CreateAnomalyGraph(ParentProcData)
11:     EdgeDataParentProc=LeadershipDensity(EvaluationGraph)
12:   end for
13:   for proc in edge do
14:     ProcData=SplitTime(proc,Time)
15:     EvaluationGraph=CreateAnomalyGraph(ProcData)
16:     EdgeDataProc=LeadershipDensity(EvaluationGraph)
17:   end for
18:   Anom, MalScore=CombineData(EdgeDataParentProc,EdgeDataProc)
19: end for
20: return  Anom, MalScore
```

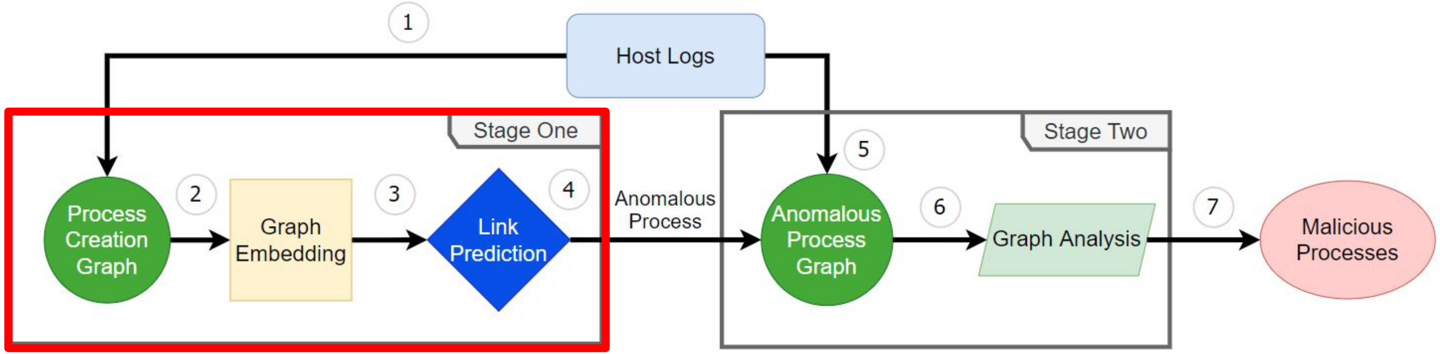
ProcAID Stage One

- **Goal:** Find anomalous process creations
- **Method:** Model user and process interactions
- Key Characteristics:
    - Node2Vec Embedding
    - Logistic Regression

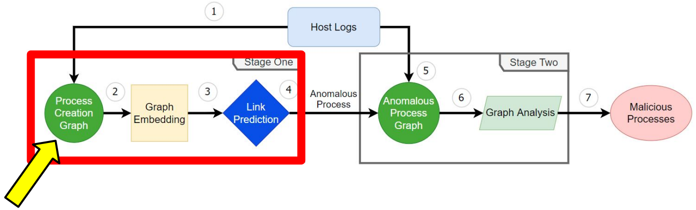
Algorithm 1 ProcAID Algorithm

Input: HostLogs
Output: Anom,MalScore

```
//Stage One
ProcGraphTrain=CreateGraph(CreateProcTrain)
ProcGraphTest=CreateGraph(CreateProcTest)
ProcAnomalies=GraphAnomaly(ProcGraphTrain,ProcGraphTest,Thres)
//Stage Two
MalEdgeCollection=FindLogs(ProcAnomalies)
for edge in MalEdgeCollection do
  for parentproc in edge do
    ParentProcData=SplitTime(parentproc,Time)
    EvaluationGraph=CreateAnomalyGraph(ParentProcData)
    EdgeDataParentProc=LeadershipDensity(EvaluationGraph)
  end for
  for proc in edge do
    ProcData=SplitTime(proc,Time)
    EvaluationGraph=CreateAnomalyGraph(ProcData)
    EdgeDataProc=LeadershipDensity(EvaluationGraph)
  end for
  Anom, MalScore=CombineData(EdgeDataParentProc,EdgeDataProc)
end for
return Anom, MalScore
```

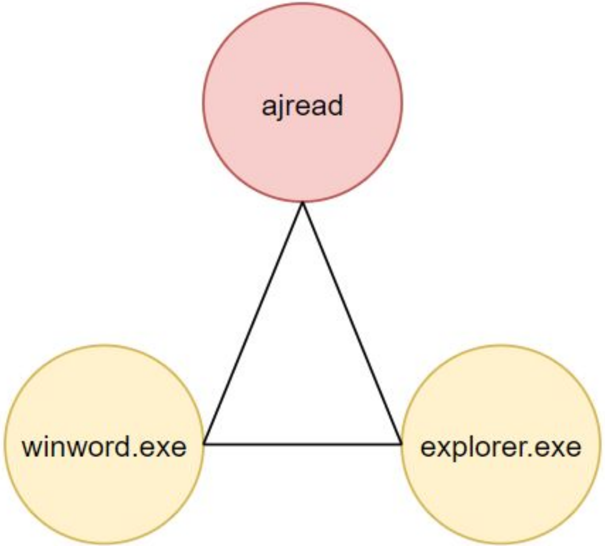


Stage One: Graph Creation

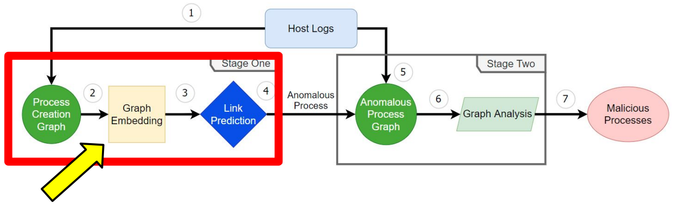


- Form two Process Creation Graphs (train and test) with host logs
- Graph Schema
  - Nodes: User, Process Path, or Parent Process Path
  - Edges: Executions/interactions

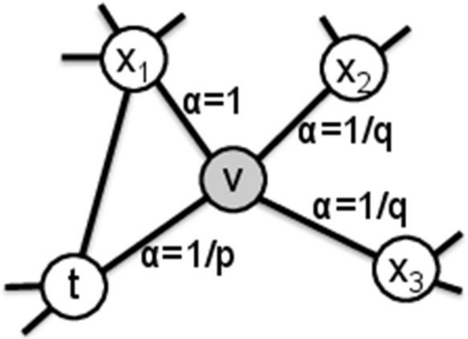
Example: User "ajread" spawns "winword.exe" from "explorer.exe"



Stage One: Graph Embedding



- Learn information from training Process Creation Graph through embedding
- Random walks
  - *node2vec: Scalable feature learning for networks*[1]
  - Second order parameters
    - *p*: return parameter
    - *q*: in-out parameter
  - Depth-first search: high *p*, low *q*
  - Breadth-first search: low *p*, high *q*
- Focus on local neighborhood vs. larger network
- Hadamard embedding of edges



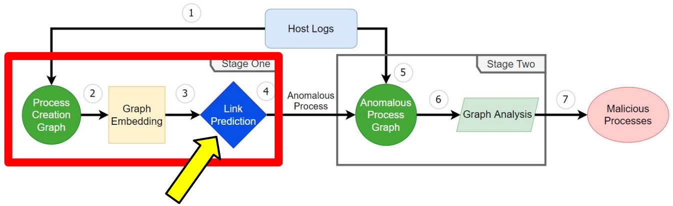
node2vec: Scalable feature learning for networks[1]

$$[f(u) \boxdot f(v)]_i = f_i(u) * f_i(v)$$

node2vec: Scalable feature learning for networks[1]

[1]A. Grover and J. Leskovec, “node2vec: Scalable feature learning for networks,” in Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 855–864, 2016.

Stage One: Link Prediction



- Predict existence of test graph edges
- ML Algorithm: Logistic Regression
  - Quick training time
  - Well calibrated probabilities
    - *Pe*=0, edge does not exist
    - *Pe*=1, edge does exist

$$p_e = \frac{1}{1 + \exp^{-x*T}}$$

- Prediction Threshold (τ)
  - Edge anomaly if probability less than threshold

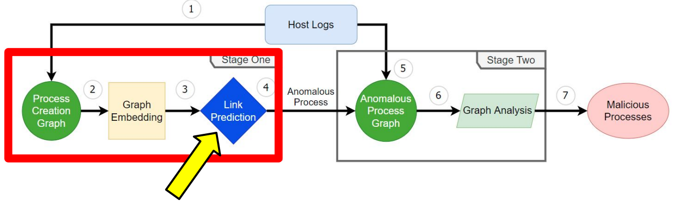
$$e_{anom} = \begin{cases} 1 & p_e < \tau \\ 0 & \text{otherwise} \end{cases}$$

Dataset

- Operationally Transparent Cyber Data Release (OpTC)
- 1000 hosts with multiple days of benign and malicious activity
- Logs formulated into “object” and “action” pairs for analytics

Host	Type of Exploitation	Post-Exploitation Actions
0201	Batch file containing Powershell code	PowerShell Empire, Mimikatz, registry edits
0501	Phishing with Macro-enabled Word Document	DeathStar, PowerShell Empire, Windows Management Instrumentation (WMI) subscriptions, SSH forwarding

Stage One Evaluation Metrics



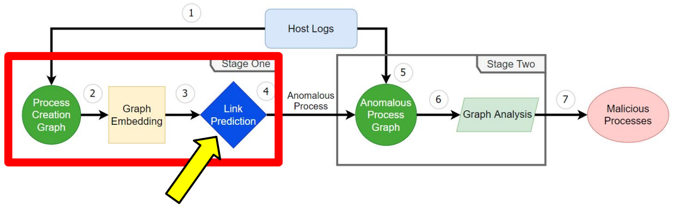
- Metrics:
  - True Positive: edge **found in** Process Creation Graph that is present **in** Red Team notes
  - False Positive: edge **found in** Process Creation graph that is **not in** Red Team notes
  - False Negative: edge **not found in** Process Creation graph that is **in** Red Team notes
  - True Negative: edge **not found in** Process Creation graph that is **not in** Red team notes
- Important: Red Team notes do not track all Red Team activity

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} = \frac{RedTeam_{edge}}{RedTeam_{edge} + RedTeam'_{edge}}$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} = \frac{RedTeam_{edge}}{RedTeam_{edge} + RedTeam_{edge'}}$$

$$F1_{Score} = 2\frac{Recall * Precision}{Recall + Precision}$$

Stage One Evaluation Results



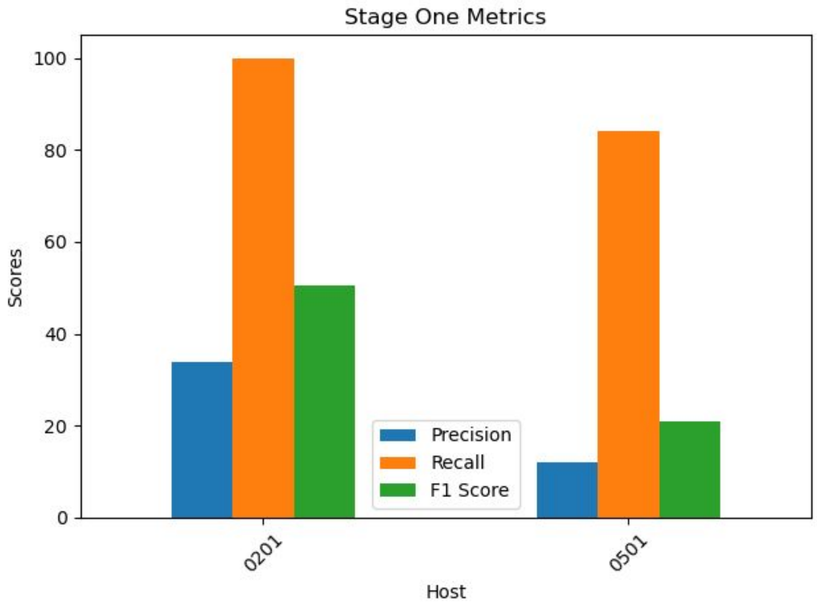
Host 0201

- ProcAID discovers all malicious process creation events
- False positives impact precision

Host 0501

- ProcAID discovers majority of malicious process creation events
- Overwhelmed by false positives

<u>Conclusion:</u> Engineer Stage Two to intelligently filter false positives



Host	Precision	Recall	F1 Score
0201	33.871	100.00	50.602
0501	11.852	84.211	20.779

Stage One: Link Prediction Threshold Optimization

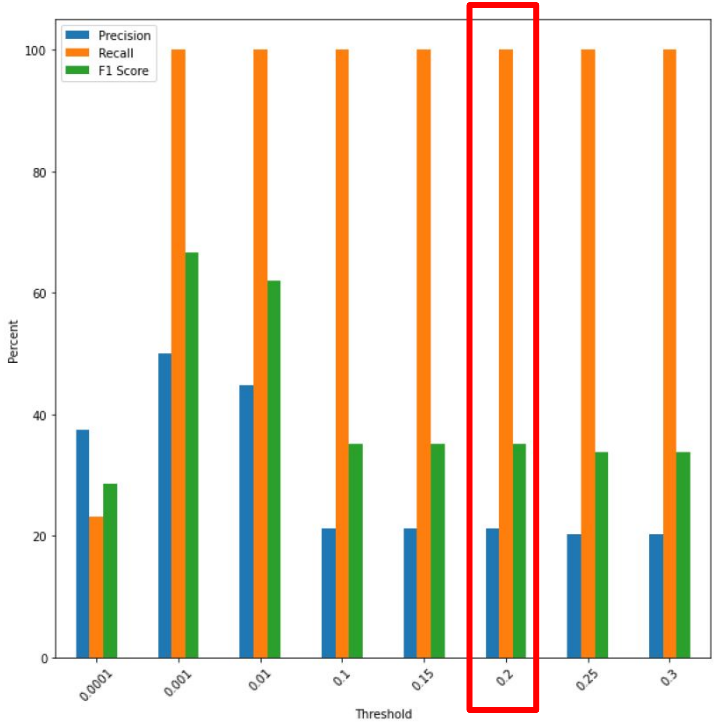


Figure 4.7: Host 0201 τ Evaluation

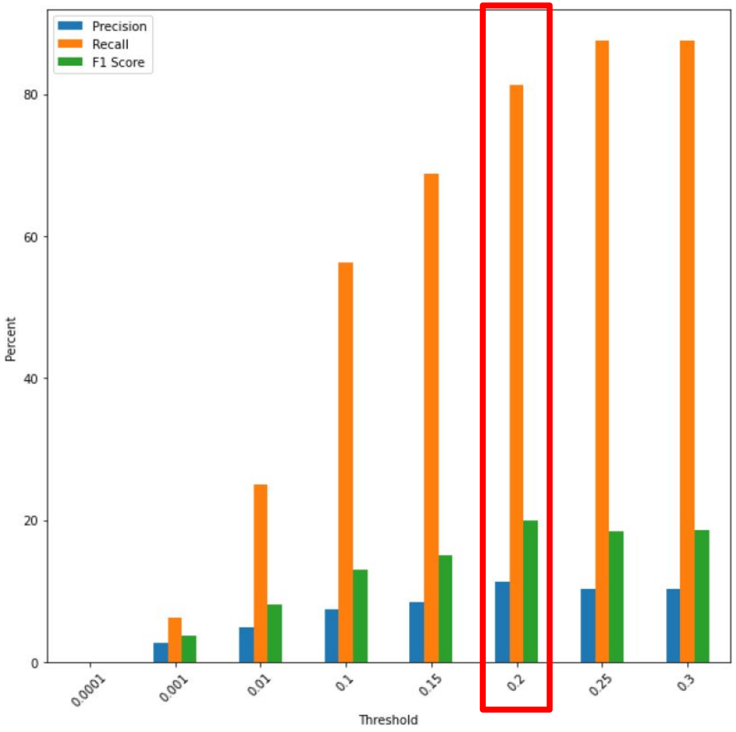


Figure 4.8: Host 0501 τ Evaluation

τ=0.20

P_e=0 P_e=1

Stage One: Random Walk Optimization

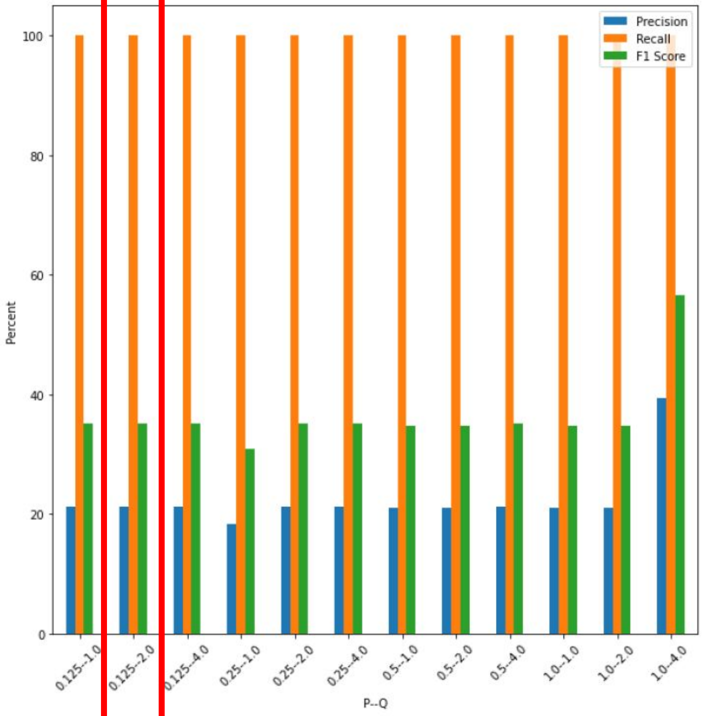


Figure 4.5: Host 0201 Random Walk Evaluation

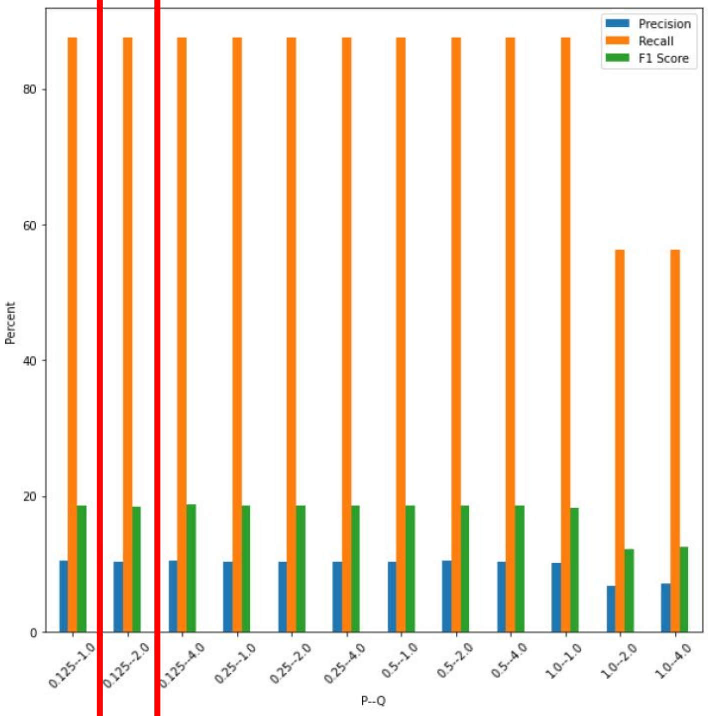
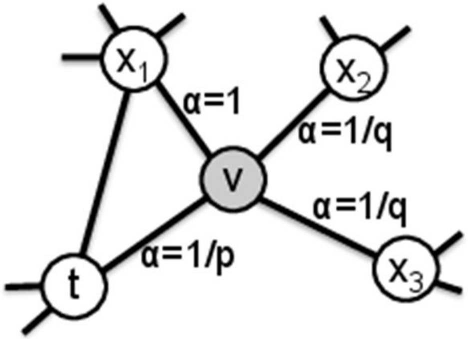


Figure 4.6: Host 0501 Random Walk Evaluation



ProcAID: Stage Two

- **<u>Goal:</u>** Scrutinize anomalous process from Stage One
- **<u>Method:</u>** Examine anomalous edges using graph analytics
- Substages
  - Data Preparation
    - Formats data for Graph Creation
  - Graph Creation
    - Anomalous Process Graph creation
  - Analysis
    - Inverse Graph Leadership
    - Inverse Graph Density

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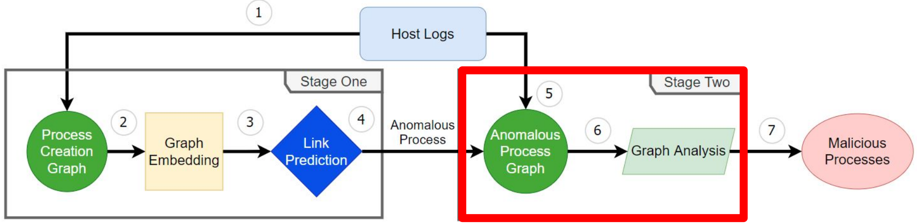
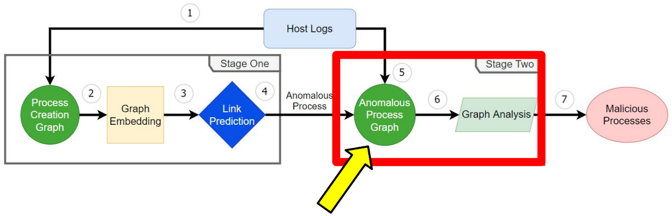
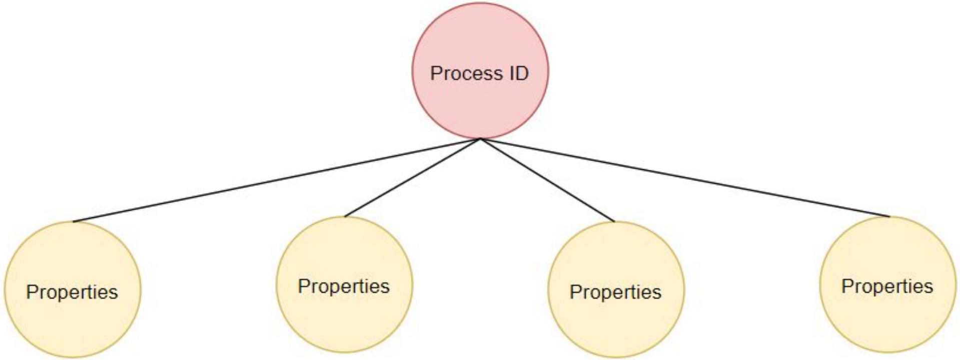


Stage Two: Graph Creation



- **<u>Purpose:</u>** Model process entire interaction with host

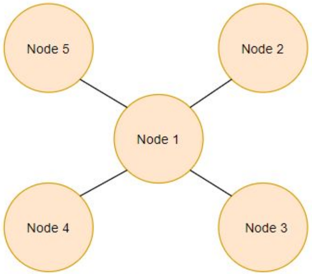
- Graph Schema
  - Nodes: PID, Parent PID, Registry Values, Registry Keys, Source IP, Destination IP
  - Edges: Interactions



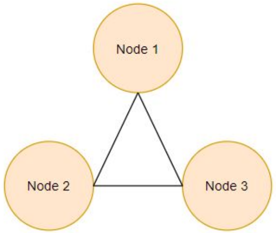
Analysis Background

- Leadership:
  - Measure of the extent of which a graph is dominated by a single node

$$L = \frac{\sum_{i=1}^{n} d_{max} - d_i}{(n-1)(n-2)}$$



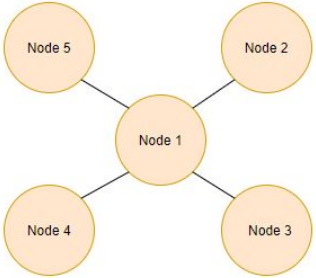
Maximal



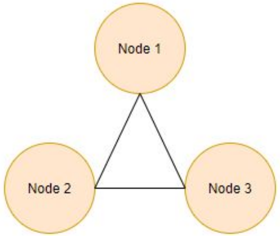
Minimal

- Density
  - Measure of the number of connections between nodes in comparison to the number of possible connections between nodes

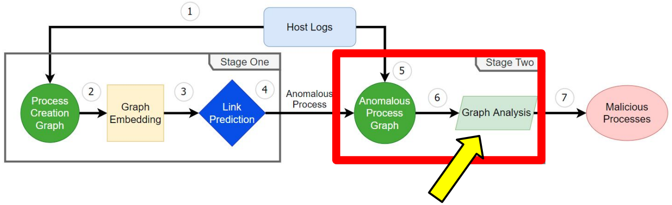
$$D = \frac{2m}{n(n-1)}$$



Density=0.40



Density=1.0



Stage Two: Analysis

Assumption 1:

- The Anomalous Process Graph for a malicious process will have a high inverse graph leadership value because process execution will be dominated by multiple objects.

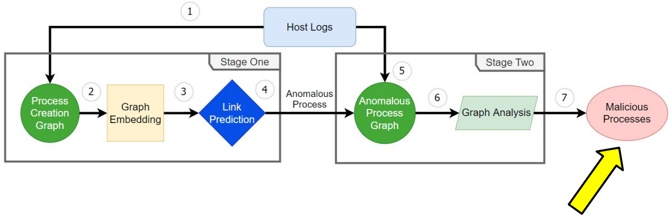
$$L^{-1} = \frac{(n-1)(n-2)}{\sum_{i=1}^{n} d_{max} - d_i}$$

Assumption 2:

- The Anomalous Process Graph for a malicious process will have a high inverse graph density value because objects will interact with a wide range of unique subjects during execution.

$$D^{-1} = \frac{n(n-1)}{2m}$$

Final Maliciousness Score



Assumption 3:

- The total maliciousness score for a malicious process will be higher than the total maliciousness score for a benign process.

$$MalScore_{process} = \sum_{i=0}^{N} [L^{-1}[i] + D^{-1}[i]]$$

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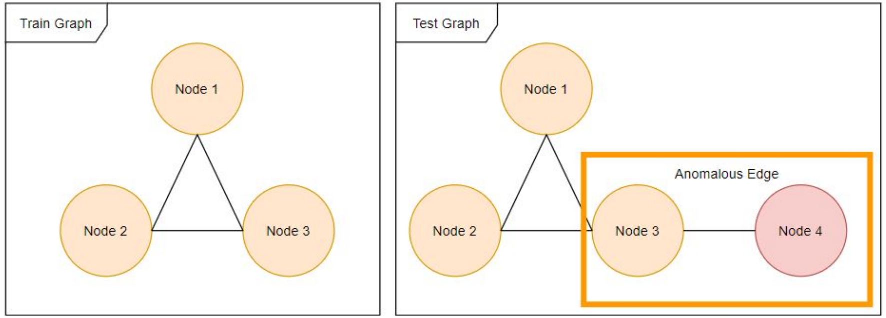
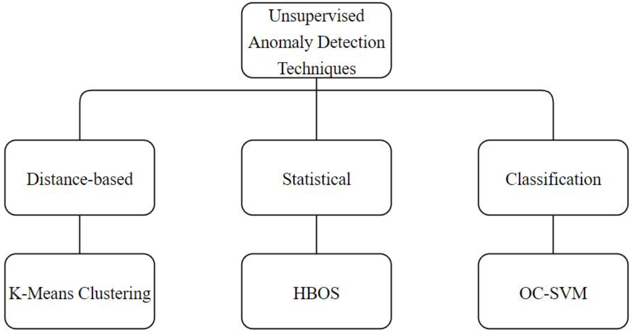
Algorithm Comparison

- Independent Variables:
  - Training and Testing Data
  - Features: user, process path, and parent process path
- NewEdge Graph Algorithm
  - Returns new edges found in the Test Graph that are **not** in the Training Graph
    - Key: No threshold

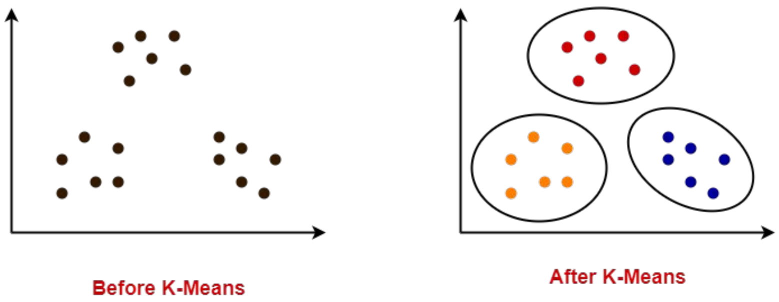


- Unsupervised ML Algorithm:
  - Distance-based: K-Means Clustering
  - Statistical: Hierarchical Based Outlier Score (HBOS)
  - Classification: One-Class Support Vector Machine (OC-SVM)



Algorithm Comparison: K-Means Clustering

- Algorithm
  - Iterative assignment of data points to clusters



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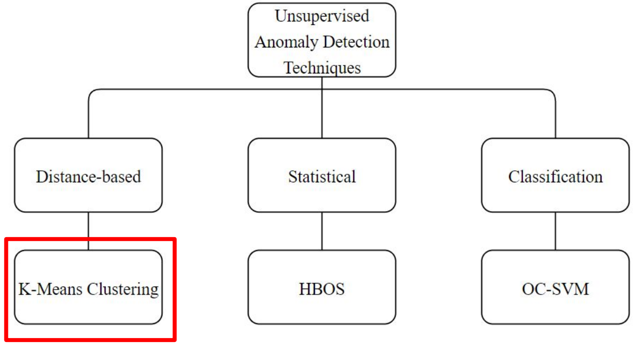
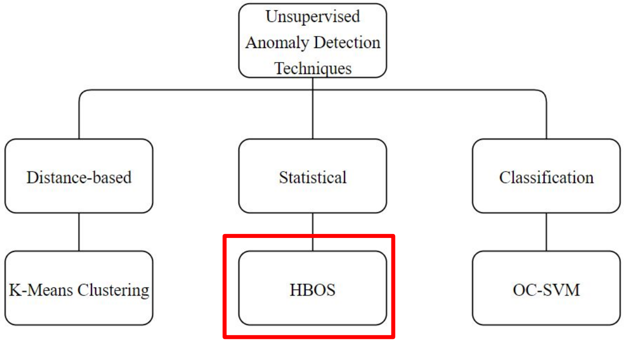


- Anomaly Definition:
  - Data with large distance to assigned centroid

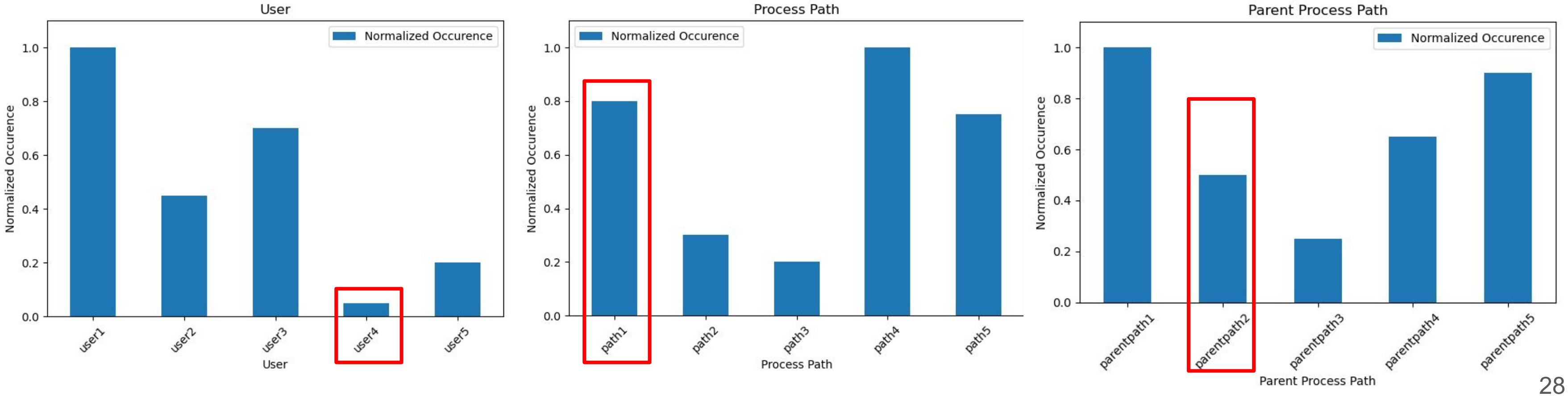
$$e_{anom} = \begin{cases} 1 & e_{euclid} \in \tau_d \\ 0 & \text{otherwise} \end{cases}$$

Algorithm Comparison: HBOS

- Algorithm
  - Frequency calculation of features
  - Logarithmic sum of histograms creates score
- Anomaly Definition:
  - Highest scores represent the most anomalous activity



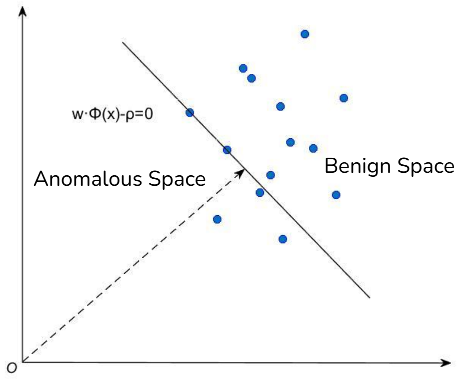
$$HBOS_{instance} = \sum_{i=0}^{d} \log \frac{1}{hist_i(instance)}$$

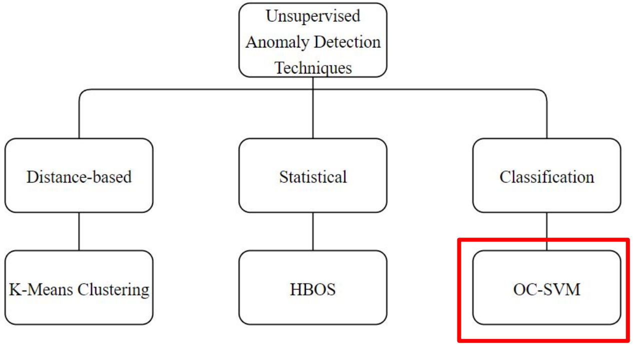


Algorithm Comparison: OC SVM

- Algorithm:
  - Learns a decision boundary to group input data

$$g(x) = \omega^T \phi(x) - \rho$$

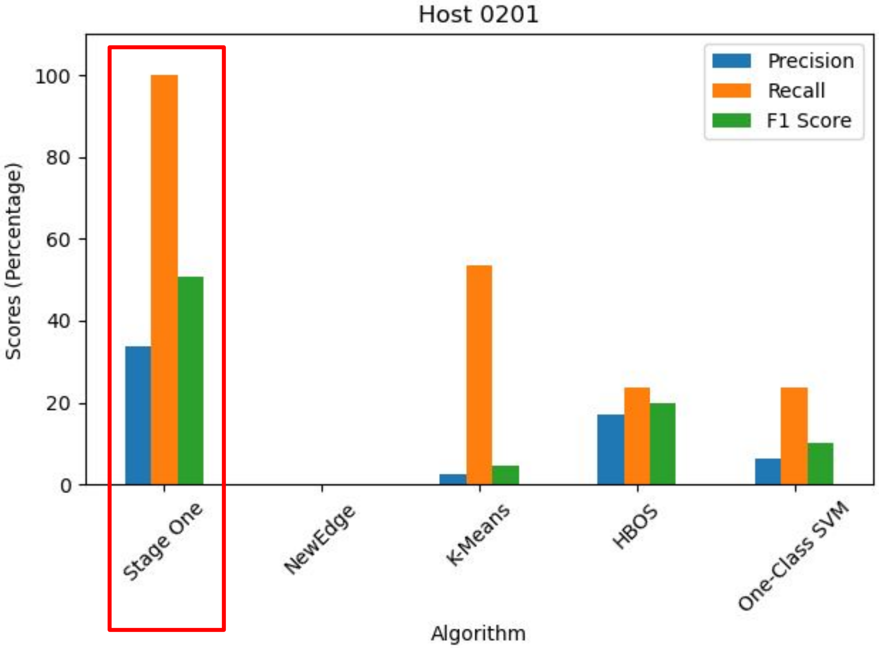


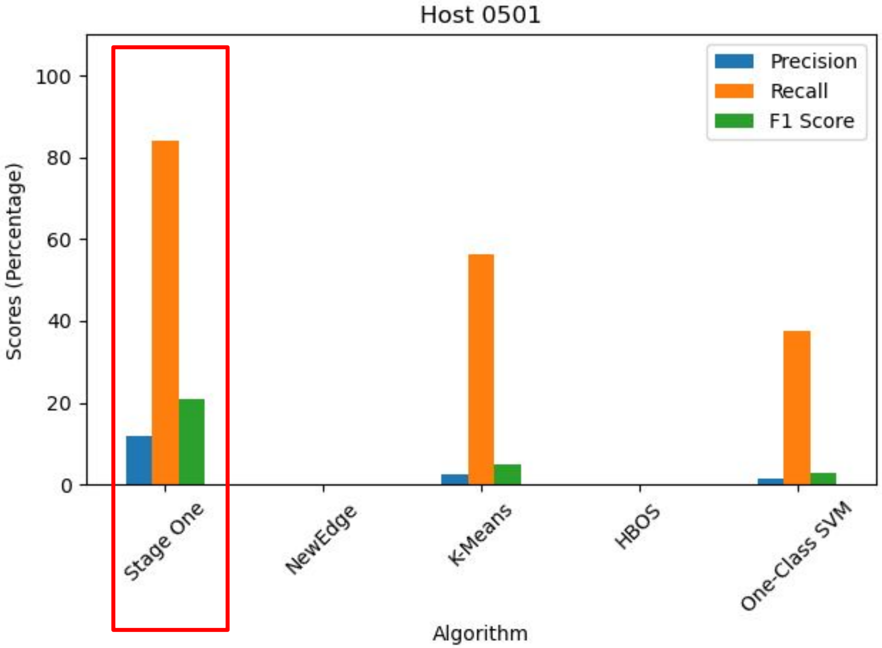


- Anomaly Definition:
  - Any data point below the learned linear boundary is an anomaly
  - No threshold

$$label = \begin{cases} anomalous & \text{if } g(x) < 0 \\ benign & \text{if } g(x) > 0 \end{cases}$$

Algorithm Comparison Results





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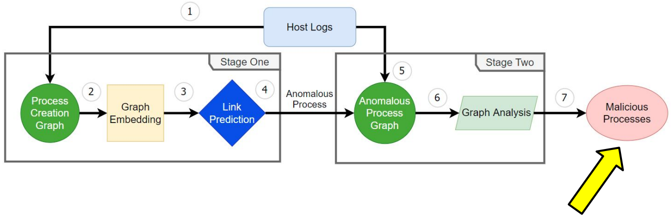
Results for Host 0201



- Placement of malicious activity at the highest percentiles of the results
    - Assumption 3 is affirmed
- Effectively filters false positives from Stage One
- Processes:
    - 4632, 2952, 1284
- Average Run Time: 30.966 sec

Threshold	Precision	Recall
Top 1	1.000	0.500
Top 5	0.800	0.800
Top 10	0.600	0.857
Top 15	0.467	1.000
Top 20	0.400	1.000

Table 4.8: Top-K Comparison for Host 0201

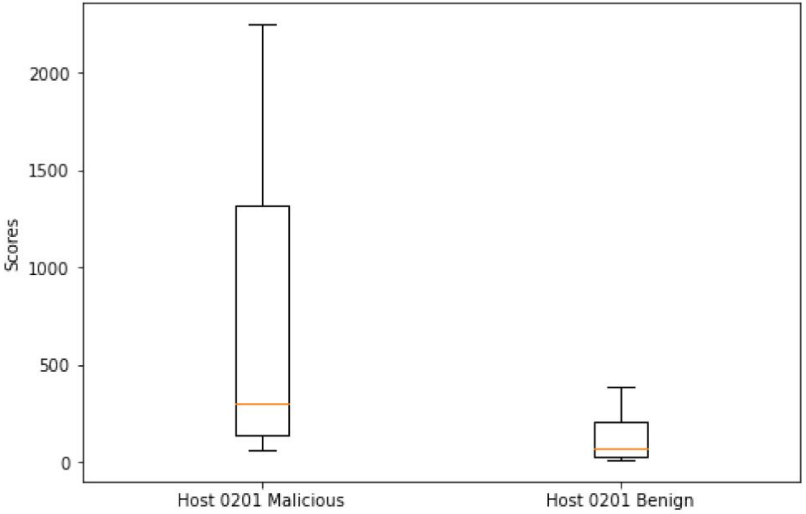
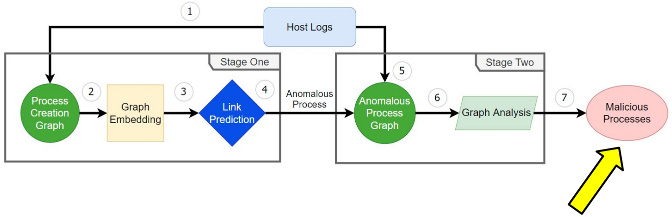


Figure 4.9: Box and Whisker Plot for Scores on Host 0201



Results for Host 0501

- Increased number of false positives impact results
- Placement of malicious activity at higher percentiles of results
  - Assumption 3 is affirmed
- Processes:
  - 2804 (5076), 1748, 648
- Average Run Time: 268.23 sec

Threshold	Precision	Recall
Top 1	0.000	0.000
Top 5	0.800	1.000
Top 10	0.400	1.000
Top 15	0.267	1.000
Top 20	0.200	1.000

Table 4.10: Top-K Comparison for Host 0501

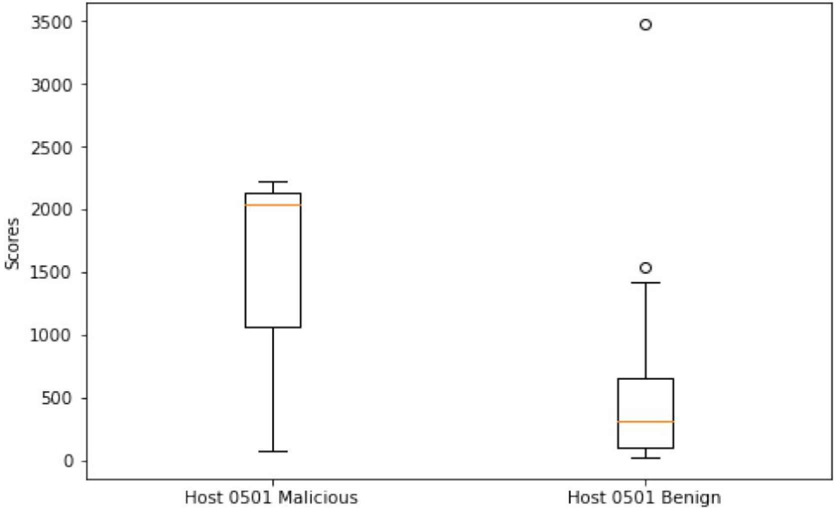
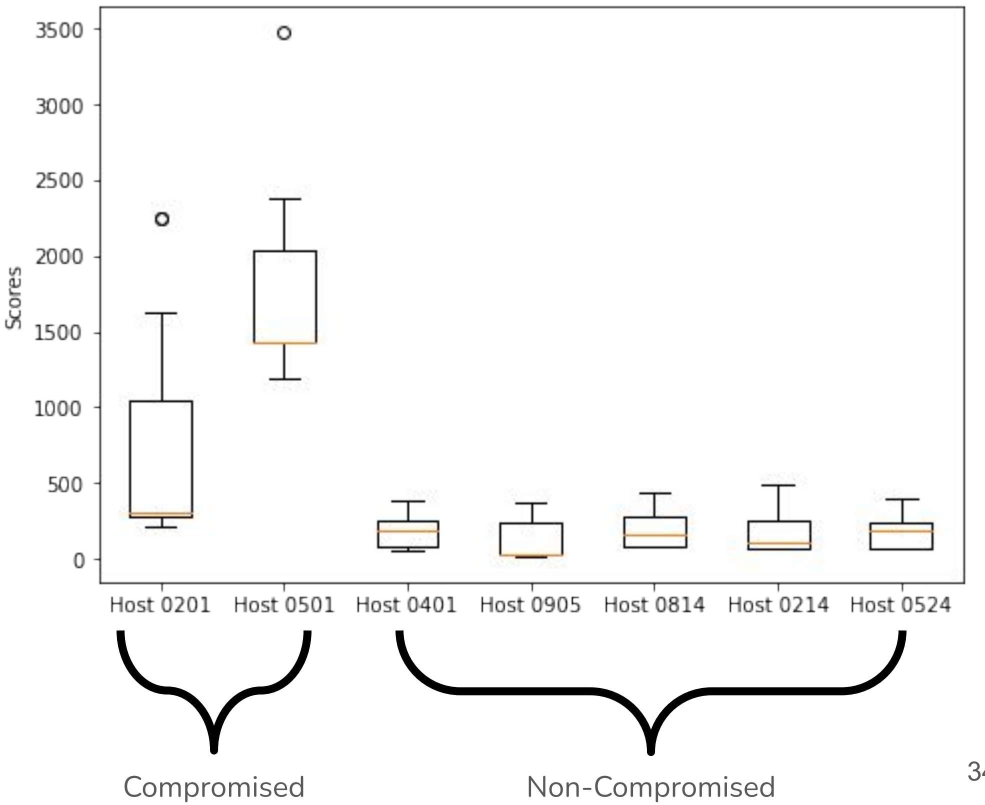


Figure 4.10: Box and Whisker Plot for Scores on Host 0501

ProcAID Results Across Multiple Hosts

- Enterprise Implementation
- Scores reflect both malicious and benign processes
- Compromised hosts show clear increased mean and standard deviation

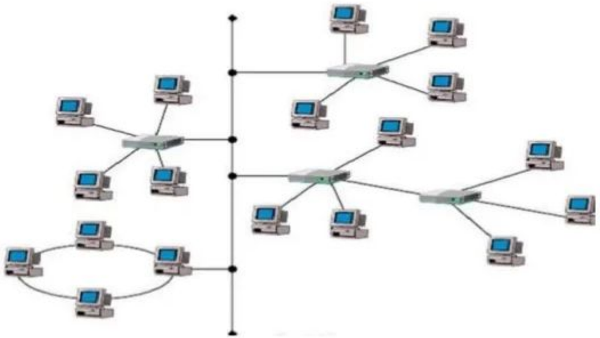


Agenda

- Motivation and Challenges
- Methodology
- Algorithm Comparison
- Results
- Future Work
- Implications and Conclusion

Future Work

- Graph embedding techniques other than Node2Vec
- Datasets
    - Los Alamos National Laboratory (LANL) Dataset
    - Any verbose dataset with Windows Security Event ID 4688 or similar
- Full enterprise implementation
    - Placement of users and administrators based on process creation activity in Stage One



https://techgenix.com/network-topology/

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https://csr.lanl.gov/

Agenda

- Motivation and Challenges
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Implications and Conclusions

Implications

- ProcAID application is simple and vast in the cybersecurity space
  - No rule creation, no supervision
  - However, training required

Conclusion

- Fusion of unsupervised link prediction, inverse graph leadership, and inverse graph density
- Efficient and effective host-based anomaly detection system for combatting APTs

Questions?

Supplemental Slides