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Benign Activity Extraction for Dependency Reduction in Data Provenance-based Attack Analysis

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Attack Detection Solutions

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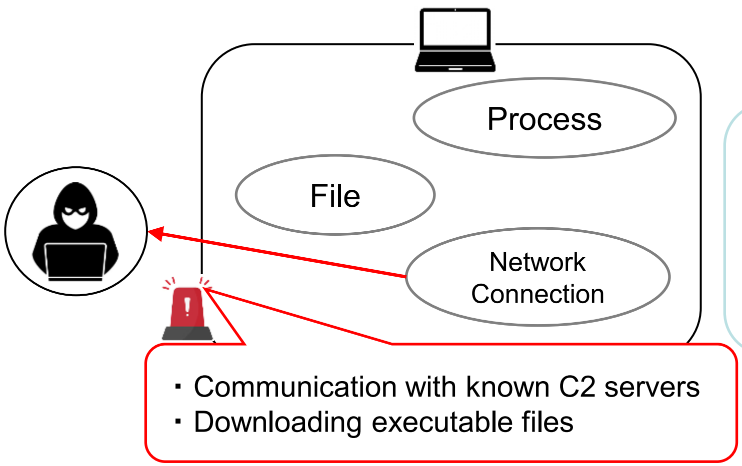
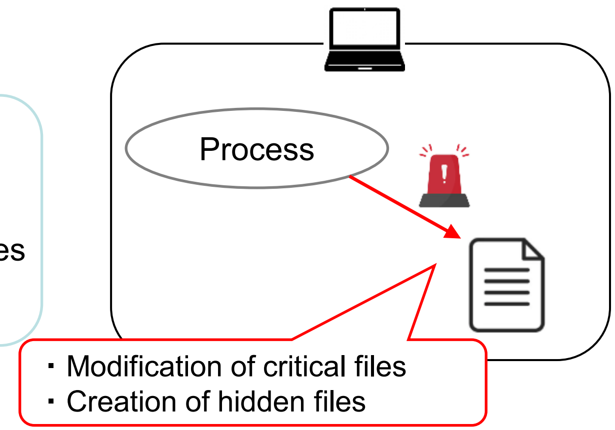
Conventional Attack Detection Solutions(Rule-based)

- Detection rules based on a single event



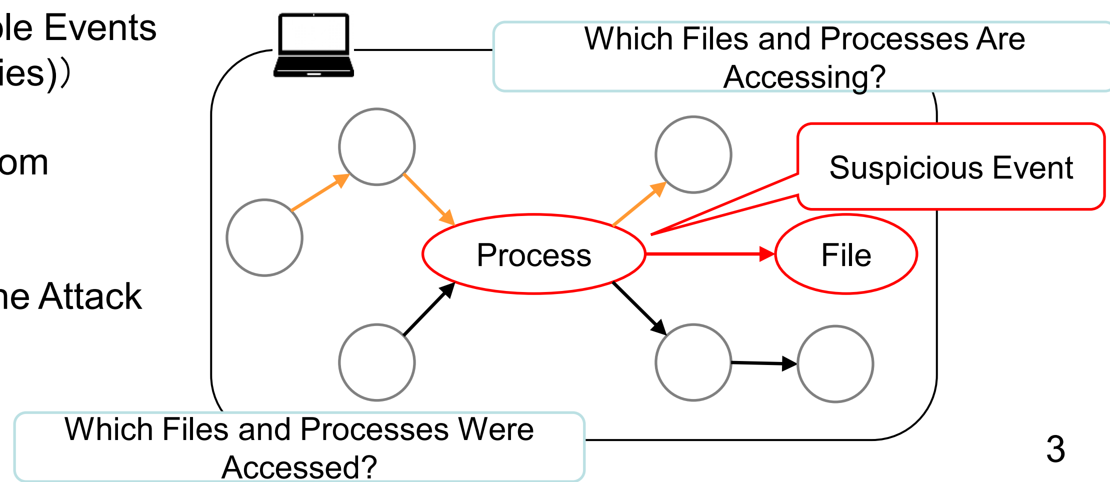
Difficult to Determine Whether It Is Truly an Attack

・Contains Legitimate User Activities
・Outdated IoC information



Recent Systems (Provenance-based IDS/EDR)

- Tracking Dependencies Among Multiple Events ((Identifying Activities))
- Determining Whether It Is an Attack from Activities Around Suspicious Events
- Identifying the Source and Scope of the Attack



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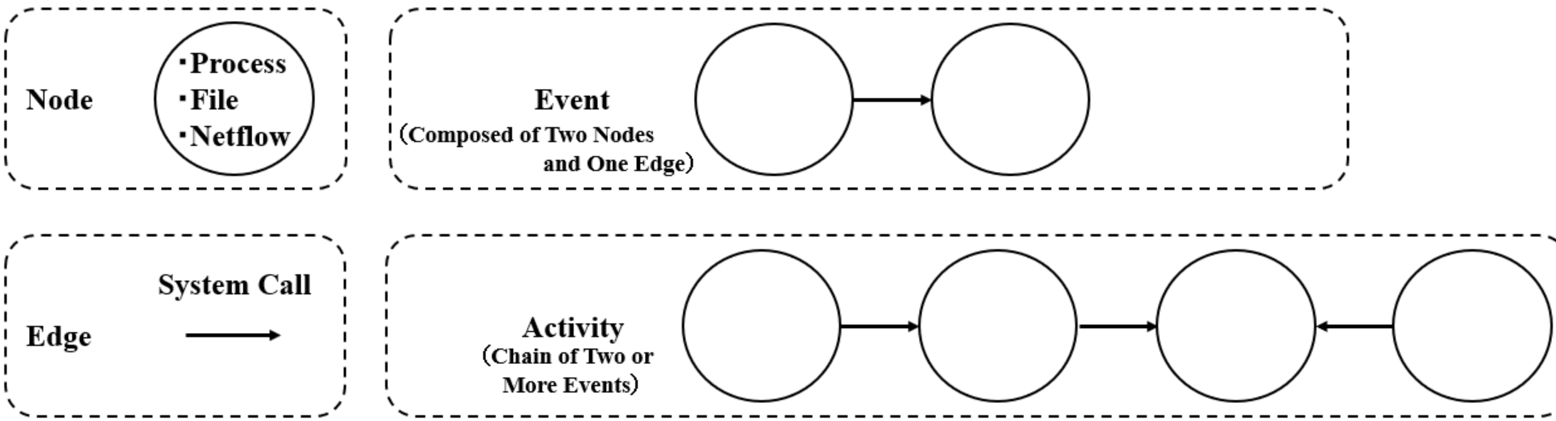
Data Provenance[1]

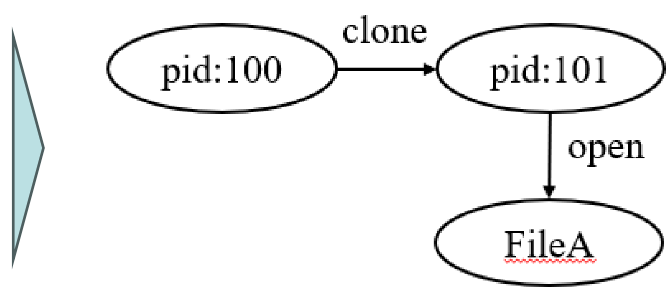
From where was a process or file generated or moved?

→ Trace the origin of the data, link related entities, and visualize them as a graph.



Log data

- Process {uuid: ”0”, pid: ”100”, src: ”ppid:”99”}
- Process {uuid: ”1”, pid: ”101”, src: ”ppid:100”}
- File {uuid: ”2”, filename: ”FileA”}
- Event {type:”clone”, src:”uuid:0”, dst:”uuid:1”}
- Event {type:”open”, src:”uuid:1”, dst:”uuid:2”}



Log Data and Provenance Graph

[1] NIST. NIST SP 800-53 Rev. 5, Security and Privacy Controlsfor Information Systems and Organizations

Provenance Graph — Use Case

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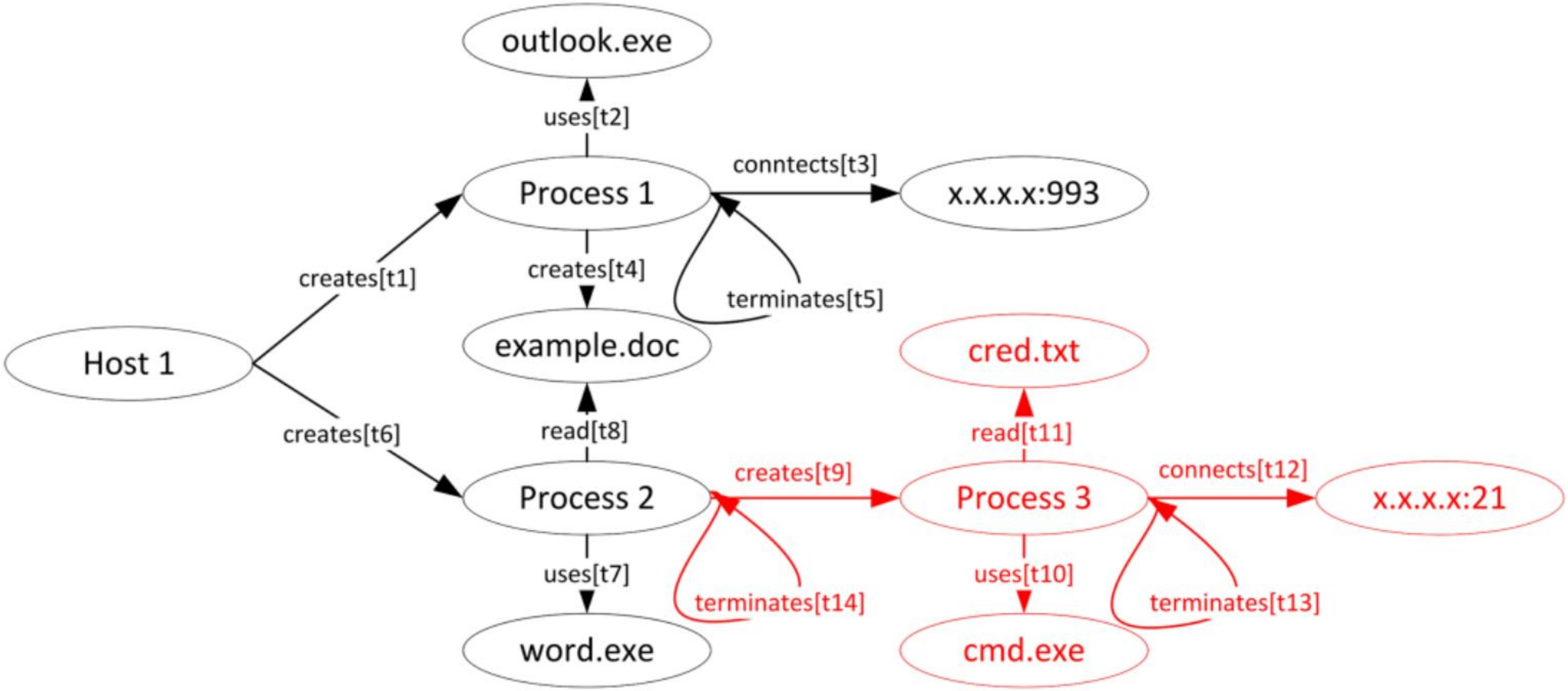

Example of a Provenance Graph exhibiting malicious activity [2]

- User reads an email using Outlook.
- User downloads an email attachment (example.doc) containing malicious code.
- User opens example.doc.
- Host spawns a process to run Word (Process 2).
- Host uses Word to open example.doc.
- Malicious code executes via Word macros.
- The malicious code leverages the existing process (Process 2) to spawn malware (Process 3).
- Malware uses the command prompt to read sensitive information (cred.txt) and exfiltrate it.

[2] Zipperle, Michael, et al. ”Provenance-based Intrusion Detection Systems: A Survey”ACM Comput. Surv. 2023

Challenge: Dependency Explosion

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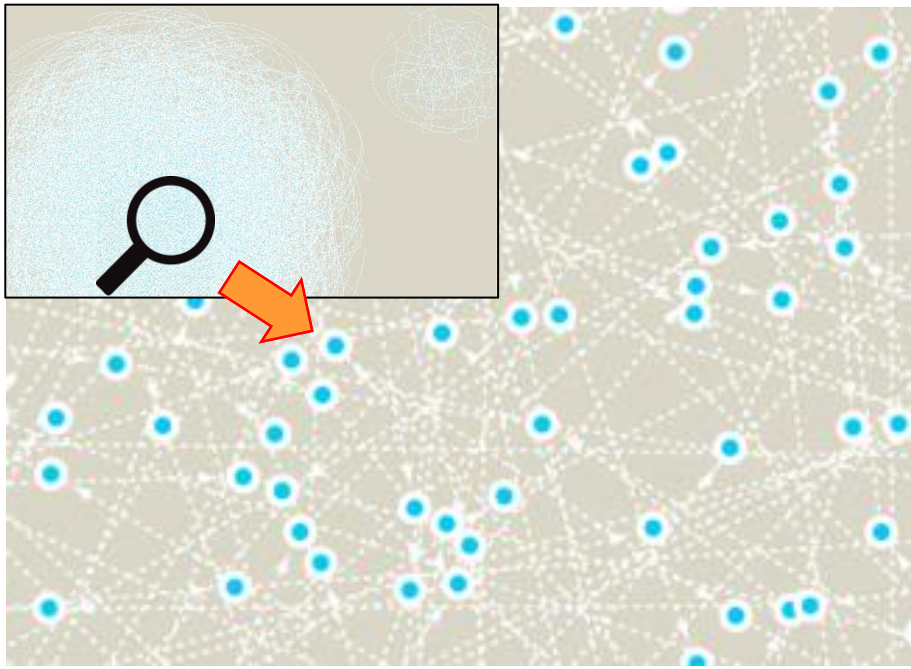

Dependency Explosion

Only attack-relevant activities

- Huge audit log volumes (e.g., several TB).
- Graphs include many dependencies unrelated to attacks.
  （Normal user actions and benign system behavior ）

→ **Result:** graphs become massive, making analysis difficult.

Ideal: Consist only of attack-relevant dependencies.

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Objective and Contribution

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Objective

Extract benign activities within computer systems and reduce dependencies.

Contribution

- Propose a method to extract benign activities from log data and remove them from dependency graphs.
  ※ To our knowledge, this is the first attempt at dependency reduction itself.
  ※ Previous studies focused on removing benign events (single events) or extracting malicious activities.
- Demonstrate that approximately **6.8%–39%** of system activities can be defined as benign activity patterns.
- Show that using benign activities extracted from about **1～3%** of the log data can reduce dependencies by up to **52.3%**, indicating that a small amount of data can be used to shrink the search space in large-scale datasets.
- Analyze the **DARPA public dataset** and estimate the characteristics of each dataset.

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Related Work

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Research proposing a method to reduce dependency explosion.

Name(Conference)	Year	Method	Dataset
LogGC (CCS)	2013	●Exclusion of temporary file deletion events	Original
CPR (CCS)	2016	●Merging of duplicate events	Original
NODOZE (NDSS)	2019	■Weighting based on anomaly scores	Original
DEPIMPACT (USENIX)	2022	■Weighting based on data flow volume and timing	DARPA TC + Original
NODLINK (NDSS)	2024	■Calculation of anomaly scores using NLP and VAE	Original

● Removal of Benign Events

■ Malicious Activity Identification via Weighting

Removal of Benign Events

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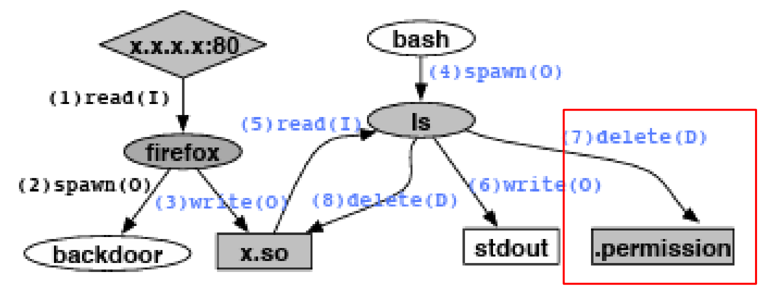
Remove benign events that do not affect analysis from the graph.

<u>LogGC[3]: Removal of Benign Events</u>

- About 23.8% of all log data consists of **temporary file deletion events**.
- These events are excluded from the dependency graph in advance.
- Temporary files are those handled by only one process during their lifetime.



(a)

<u>CPR[4]: Deduplicate Removal</u>

- **Integrates duplicate events**
- Reducing the number of edges

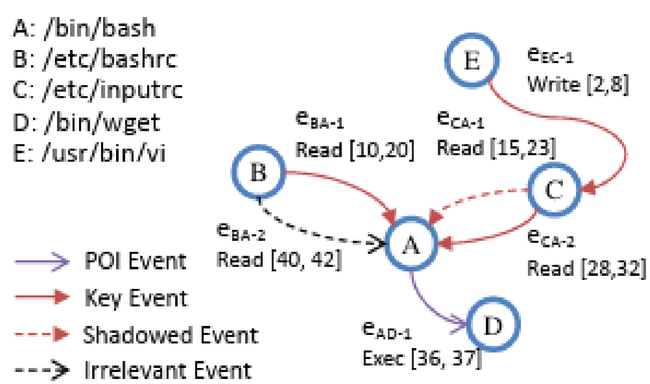


Figure 2: Unequal Dependencies in Backtracking

[3] Kyu Hyung Lee et al., LogGC: garbage collecting audit log, CCS '13: Proceedings of the 2013 ACM SIGSAC conference on Computer & communications security

[4] Zhang Xu et al., High Fidelity Data Reduction for Big Data Security Dependency Analyses, CCS '16: Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security

Malicious Activity Identification via Weighting

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Assign weights to events based on their deviation from normal behavior and propagation from known malicious nodes or edges to extract malicious activities.

- Weighting factors include distance from detection points and data flow volume.
  - Events with characteristics similar to those detected by other IDSs.
  - Events that deviate from the features of normal behavior.
  - Events with known malicious attributes (e.g., file names, IP addresses).

- Only nodes and edges judged to be related to malicious activities are retained in the graph

<u>NODLINK[5]</u>:Converts natural language information in log data into numerical vectors.

Cmmand Line	"cat /etc/tmp/log.txt"
File Path	"/etc/tmp/log.txt"
Dst IP address : Port	"126.7.8.7 : 80"

$$\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix}$$

Uses a <u>V</u>ariational <u>A</u>uto <u>E</u>ncoder (VAE) to calculate anomaly scores.

[5] Shaofei Li et al. "NODLINK: An Online System forFine-Grained APT Attack Detection and Investiga-tion". In: Proceedings 2024 Network and DistributedSystem Security Symposium.

Related Work and Our Approach

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Removal of benign events (e.g., temporary file deletions, duplicate events)

- Limited effectiveness in reducing dependencies since only part of the events are removed
- Assumes the existence of general benign events (events unnecessary for analysis).
  → **But are they truly unnecessary? This depends on the environment and analyst**.

Malicious activity identification via weighting

- Requires retraining to adapt to evolving attack behaviors.

A method is needed that can adapt to different environments and analysts
without requiring frequent retraining.

- Related work focused on **removing benign events** or **extracting malicious activities**.
- Dependency reduction through the **removal of benign activities** has not been explored.

Can we extract **system-specific benign activity patterns from log data** to reduce dependencies?

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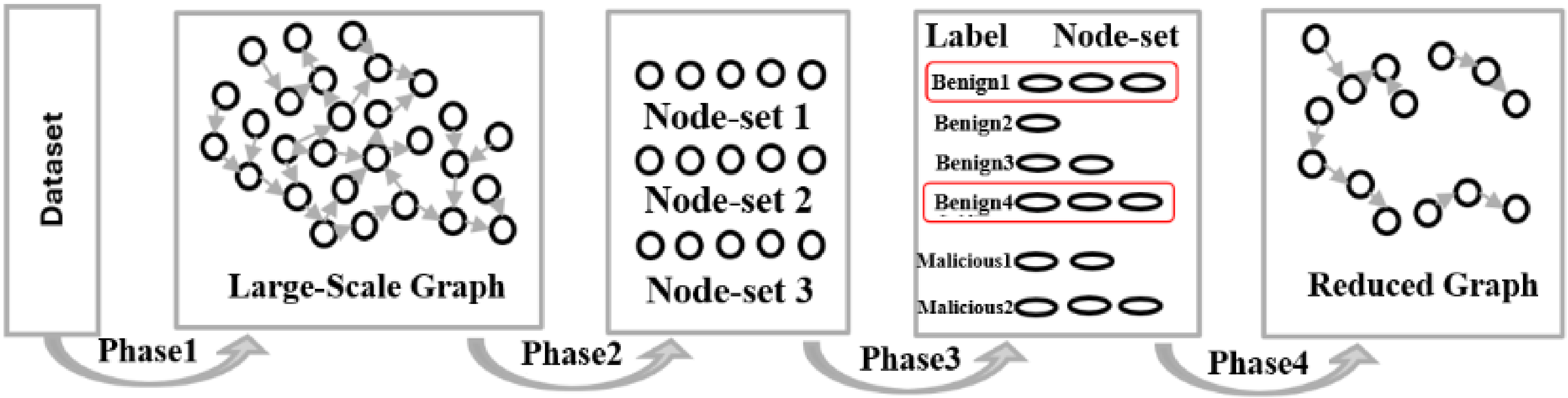
Proposed Method



Overview of the proposed method

Phase 1: Data Preprocessing
Phase 2: Node-set Construction
Phase 3: Node-set Labeling
Phase 4: Ranking Labels and Reducing Dependencies

Phase 1: Data Preprocessing

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Data Preprocessing

- Extraction of Target Edges and Nodes

Target nodes: processes, files, and network flows
Target edges: system calls used in related work[6][7] that were included in the dataset

Analysis targets

Events	System Call
Process/File	open, read, write, chmod, pipe
Process/Process	execve, clone
Process/NetFlow	recvfrom, sendto, recvmsg, sendmsg

- Extracted node information (command line, file name, IP address, and port number) for use in the next phase

- Constructed dependency graphs using the extracted data

[6] Shaofei Li et al. "NODLINK: An Online System forFine-Grained APT Attack Detection and Investiga-tion". In: Proceedings 2024 Network and DistributedSystem Security Symposium.
[7] Pengcheng Fang et al. , Back-Propagating System Dependency Impact for Attack Investigation, 31st USENIX Security Symposium (USENIX Security 22), 2022

Phase 2: Node-set Construction

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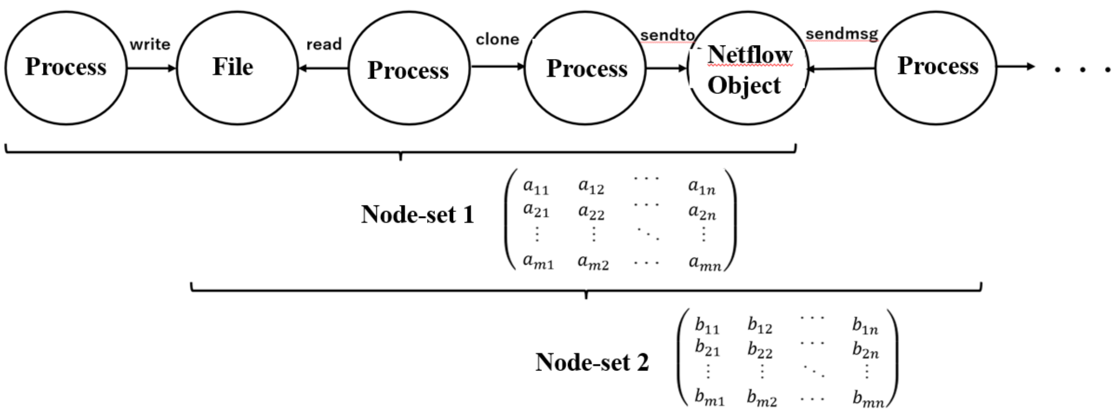
<u>Vectorization of Log Data and Construction of Node Sets</u>

- Vectorization

  Used **NODLINK** to convert command lines, file names, IP addresses, and port numbers into numerical vectors using **FastText [8]**.

- **Node-Set** Construction

  Extracted subgraphs consisting of five nodes to form each node set.



- Calculated feature values based on NODLINK's method:

$$V = w_c * V_c + \sum w_{f_i} * V_{f_i} + \sum w_{n_i} * V_{n_i} \qquad (1)$$

V_c, V_{f_i}, V_{n_i} : Features of command lines, files, and network flows

w_c, w_{f_i}, w_{n_i} : Weights for command lines, files, and network flows

[8] Bojanowski Piotr et al. "Enriching Word Vectors withSubword Information". In: Transactions of the Asso-ciation for Computational Linguistics 5 (Dec. 2017)

Phase 3: Node-set Labeling

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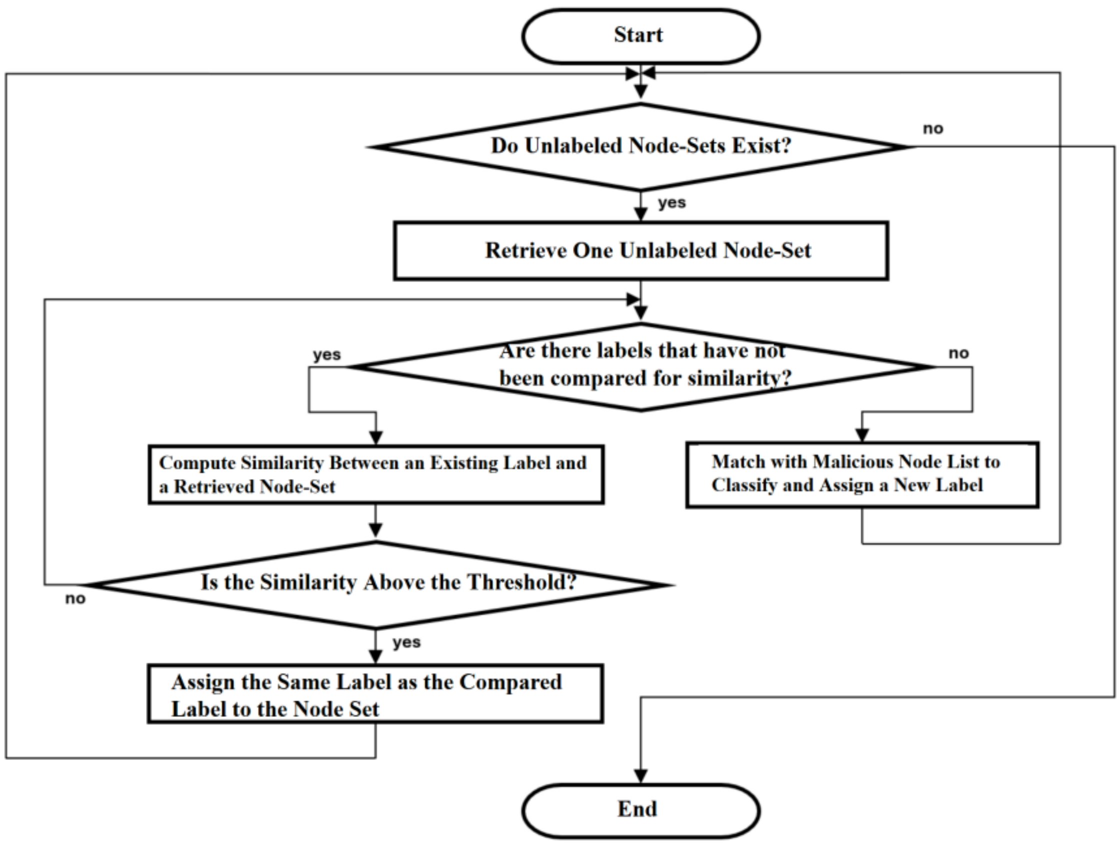
Labeling of Node Sets



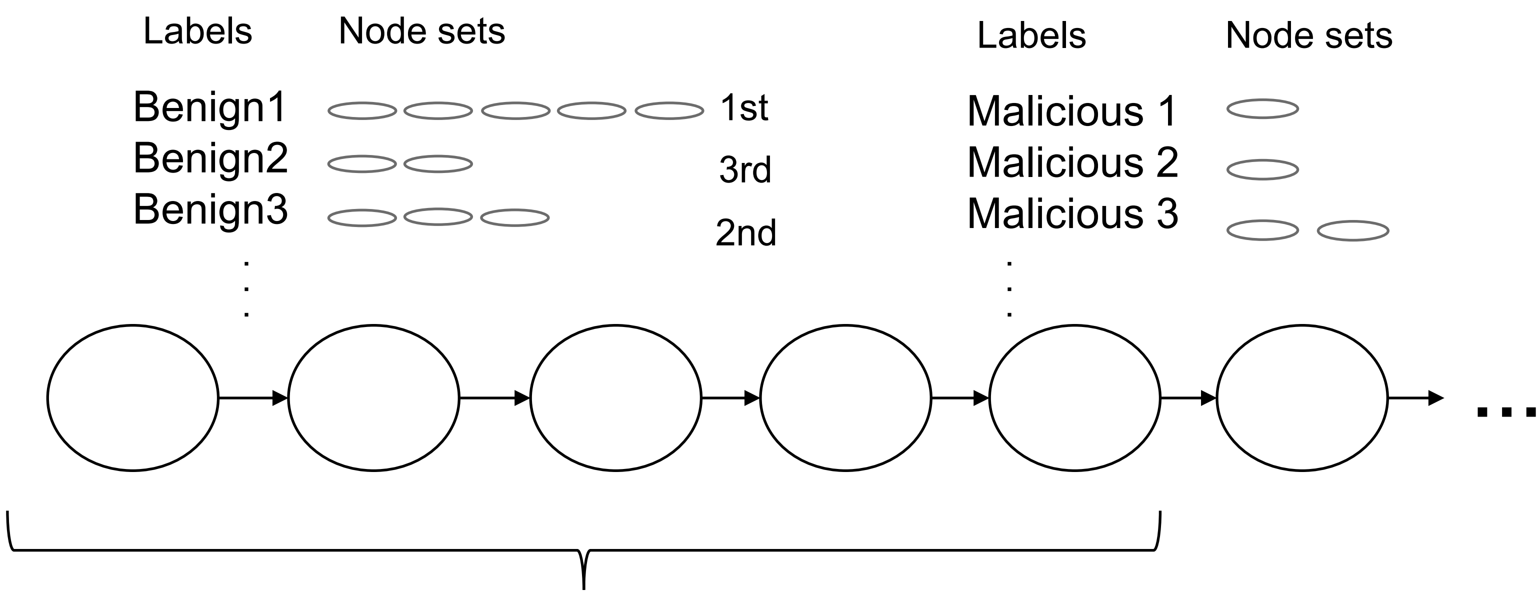
Labeling flow

- Prepared a predefined list of malicious nodes.
- If a node set contains at least one malicious node, a malicious label is assigned to that node set.
- Compare the feature vectors between node sets using cosine similarity.
- Repeat this process for all node sets.

Phase 4: Ranking Labels and Reducing Dependencies

Ranking and Dependency Graph Reduction

Remove activities similar to the top-ranked labels from the dependency graph constructed in Phase 1.



Check similarity with the **top-ranked label**.
→ If the similarity exceeds the threshold, the corresponding activity is removed from the graph.

Apply the Same Process to the Entire Graph

Set how many of the top-ranked labels are used for removal, and repeat the process for that number of labels.

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Experimental Setup

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Environment

CPU : Intel(R) Xeon(R) Silver 4314(16core/2.4GHz)

Memory: 256GB

OS : Ubuntu22.04 64-bit

Parameters

Node Set Size: 5 Nodes

Cosine Similarity Threshold: 1.0

Experiment by varying the number of top-ranked benign label types selected for removal

- From **top 3 to top 1500 label types**

Metrics

False Negative (FN): The number of malicious nodes removed from the graph

False Positive (FP): The number of good nodes left in the graph

Node Reduction Rate: $(1-\frac{\text{Number of Nodes in the Graph Before Dependency Reduction}}{\text{Number of Nodes in the Graph After Dependency Reduction}})\times 100$

Dataset

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DARPA Transparent Computing(TC) Data[9]

- Only public dataset used in previous studies
- Engagement 3 (E3) released in 2018
- Engagement 5 (E5) released in 2019
- Three datasets used: E3 Theia, E5 Theia, and E5 Marple
- Each dataset was partially extracted for training data (**three subsets: A, B, and C**)

Dataset	Data size	Proportion to Evaluation Data
E3 Theia-A	3.8GB	13.4%
E3 Theia-B	3.8GB	13.4%
E3 Theia-C	3.8GB	13.4%
E5 Theia-A	4.0GB	1.35%
E5 Theia-B	4.0GB	1.35%
E5 Theia-C	4.0GB	1.35%
E5 Marple-A	3.6GB	2.98%
E5 Marple-B	3.6GB	2.98%
E5 Marple-C	3.8GB	3.15%

E3 Theia
Log data from one Ubuntu 12.04 host (28.3 GB used for evaluation).
Includes backdoor installation exploiting a Firefox vulnerability and records of phishing emails.
(81 malicious nodes)

E5 Theia
Log data from three Ubuntu 12.04 hosts (295.8 GB used for evaluation).
Includes backdoor installation exploiting a Firefox vulnerability and communications to C2 servers.
(4 malicious nodes)

E5 Marple
Log data from one Windows 7 host (120.7 GB used for evaluation).
Includes backdoor installation exploiting a Firefox vulnerability and communications to C2 servers.
(10 malicious nodes)

[9] DARPA. TC: Transparent Computing [Online].https://www.darpa.mil/research/programs/transparent-computing. (visited on2025-01-06)

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Experimental Results: E3 Theia

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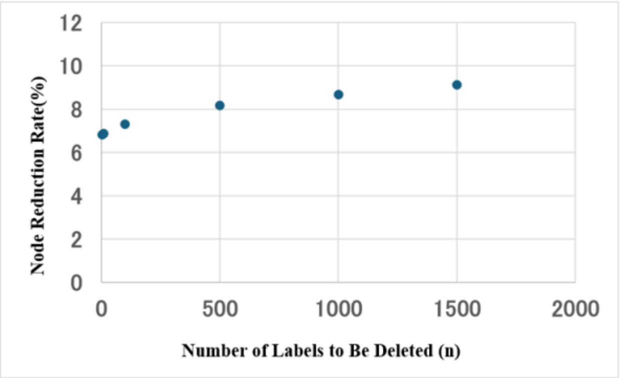
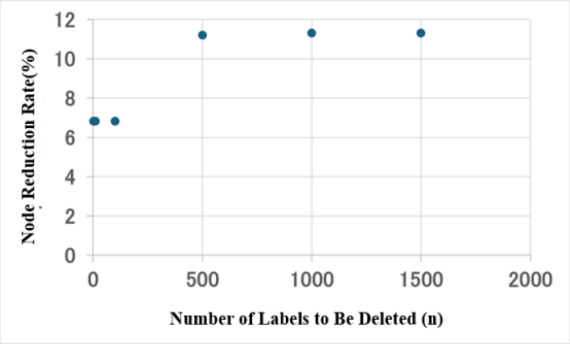
Experimental Results(E3 Theia-A)

Number of Labels to Be Deleted (n)	Node Count	FN	FP	Node Reduction Rate(%)	Execution Time(sec)
3	50,802	0	50,721	6.82	7.264
10	50,778	0	50,697	6.87	8.701
100	50,541	0	50,460	7.30	16.09
500	50,064	0	49,983	8.17	44.08
1000	49,796	0	49,715	8.67	77.24
1500	49,549	0	49,468	9.12	103.1



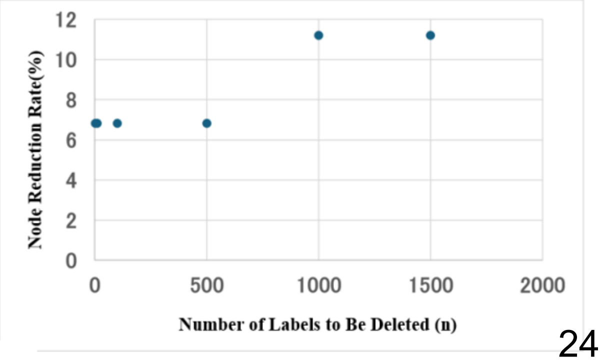
Experimental Results(E3 Theia-B)

Number of Labels to Be Deleted (n)	Node Count	FN	FP	Node Reduction Rate(%)	Execution Time(sec)
3	50,802	0	50,721	6.82	7.396
10	50,802	0	50,721	6.82	8.682
100	50,798	0	50,717	6.83	15.96
500	48,393	0	48,312	11.2	42.88
1000	48,383	0	48,302	11.3	68.49
1500	48,380	0	48,299	11.3	90.37



Experimental Results(E3 Theia-C)

Number of Labels to Be Deleted (n)	Node Count	FN	FP	Node Reduction Rate(%)	Execution Time(sec)
3	50,802	0	50,721	6.82	6.83
10	50,802	0	50,721	6.82	7.779
100	50,801	0	50,720	6.82	15.98
500	50,800	0	50,719	6.83	43.89
1000	48,398	0	48,317	11.2	69.63
1500	48,398	0	48,317	11.2	91.43



Experimental Results: E5 Theia

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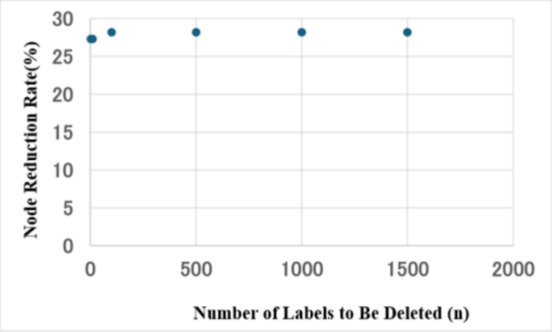
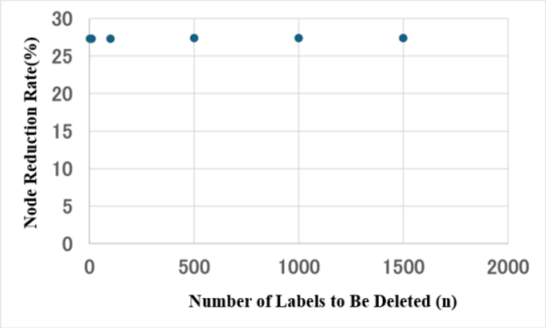
Experimental Results(E5 Theia-A)

Number of Labels to Be Deleted (n)	Node Count	FN	FP	Node Reduction Rate(%)	Execution Time(sec)
3	2,206,930	0	2,206,926	27.3	795.4
10	2,206,813	0	2,206,809	27.3	829.1
100	2,178,684	0	2,178,680	28.2	1100
500	2,177,642	0	2,177,638	28.2	1906
1000	2,177,392	0	2,177,388	28.2	2638
1500	2,177,329	0	2,177,325	28.2	3136



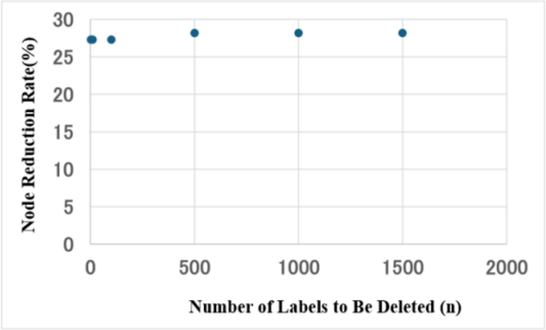
Experimental Results(E5 Theia-B)

Number of Labels to Be Deleted (n)	Node Count	FN	FP	Node Reduction Rate(%)	Execution Time(sec)
3	2,206,909	0	2,206,905	27.3	783.9
10	2,206,769	0	2,206,765	27.3	810.7
100	2,205,545	0	2,205,541	27.3	1051
500	2,204,039	0	2,204,035	27.4	1794
1000	2,203,720	0	2,203,716	27.4	2435
1500	2,203,584	0	2,203,580	27.4	2879



Experimental Results(E5 Theia-C)

Number of Labels to Be Deleted (n)	Node Count	FN	FP	Node Reduction Rate(%)	Execution Time(sec)
3	2,206,900	0	2,206,896	27.3	797.8
10	2,206,790	0	2,206,786	27.3	822.7
100	2,205,921	0	2,205,917	27.3	1,085
500	2,177,493	0	2,177,489	28.2	1,932
1000	2,177,258	0	2,177,254	28.2	2,654
1500	2,177,248	0	2,177,244	28.2	3,169



Experimental Results: E5 Marple

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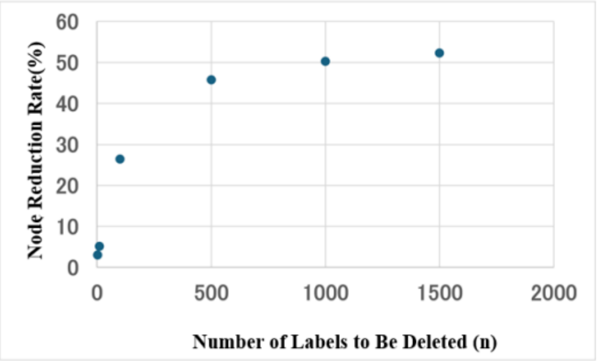
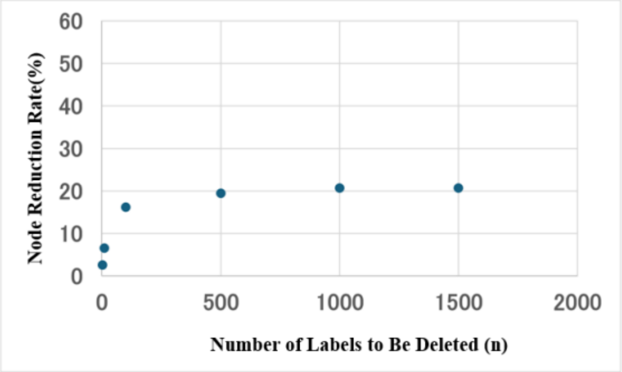
Experimental Results(E5 Marple-A)

Number of Labels to Be Deleted (n)	Node Count	FN	FP	Node Reduction Rate(%)	Execution Time(sec)
3	11,803,667	0	11,803,657	3.03	558.7
10	11,545,745	0	11,545,735	5.15	717.1
100	8,956,381	0	8,956,371	26.4	2,091
500	6,600,627	0	6,600,617	45.8	5,768
1000	6,048,300	0	6,048,290	50.3	9,130
1500	5,800,663	0	5,800,653	52.3	11,690



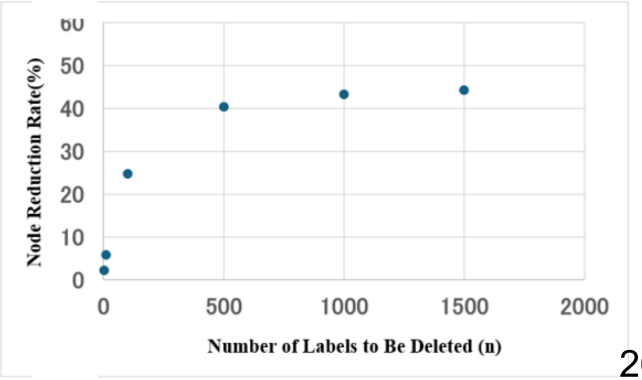
Experimental Results(E5 Marple-B)

Number of Labels to Be Deleted (n)	Node Count	FN	FP	Node Reduction Rate(%)	Execution Time(sec)
3	11,855,130	0	11,855,120	2.61	527.5
10	11,373,838	0	11,373,828	6.56	627.8
100	9,648,817	0	9,648,807	16.2	1,516
500	9,795,840	0	9,795,830	19.5	3,008
1000	9,648,817	0	9,648,807	20.7	3,603
1500	9,648,817	0	9,648,807	20.7	3,631



Experimental Results(E5 Marple-C)

Number of Labels to Be Deleted (n)	Node Count	FN	FP	Node Reduction Rate(%)	Execution Time(sec)
3	11,903,443	0	11,903,433	2.21	538.9
10	11,459,815	0	11,459,805	5.85	678.7
100	9,154,142	0	9,154,132	24.8	1886
500	7,258,716	0	7,258,706	40.4	5265
1000	6,900,864	0	6,900,854	43.3	8375
1500	6,779,474	0	6,779,464	44.3	10370



Effectiveness of Dependency Reduction

Is it possible to reduce dependencies by **extracting benign activities?**

- No false negatives were observed within the scope of this experiment
  → Node sets containing malicious nodes showed distinct features from benign labels.
- The graph reduction rate increased as the number of labels selected for removal increased.

Dependency reduction based on benign activities is feasible.

How much can dependencies be reduced?

- The maximum reduction rate in this experiment was **52.3%**.
- Based on the average reduction rates across datasets, approximately **6.8%–39%** of dependencies were identified as frequent benign activities within computer systems.
- Using about **13%** of the total log data for benign activity extraction (E3 Theia) resulted in a lower average reduction rate than using only **1.4–3.2%** of the data (E5 Theia, E5 Marple).
  → A small portion of the log data is sufficient for extracting benign activities.

Experimental results using **E5 Marple-A**.

Labels	Node Count	FN	FP	Node Reduction (%)	Exec. Time (sec)
3	11,803,667	0	11,803,657	3.03	558.7
10	11,545,745	0	11,545,735	5.15	717.1
100	8,956,381	0	8,956,371	26.4	2.091
500	6,600,627	0	6,600,617	45.8	5.768
1000	6,048,300	0	6,048,290	50.3	9.130
1500	5,800,663	0	5,800,653	52.3	11.690

Average reduction rate and execution time for each dataset.

Dataset	Avg. Reduction Rate (%)		Avg. Execution Time (sec)	
	Min ($n = 3$)	Max ($n = 1500$)	Min ($n = 3$)	Max ($n = 1500$)
E3 Theia	6.82	10.5	7.16	95.0
E5 Theia	27.3	27.9	792	3061
E5 Marple	2.62	39.1	542	8563

Dataset Features and Their Impact

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Highest Average Reduction Rate

- 3 labels → **E5 Theia**
- 1500 labels → **E5 Marple**
- **E3 Theia** showed a lower rate than the other two datasets

Dataset	Avg. Reduction Rate (%)		Avg. Execution Time (sec)	
	Min ($n=3$)	Max ($n=1500$)	Min ($n=3$)	Max ($n=1500$)
E3 Theia	6.82	10.5	7.16	95.0
E5 Theia	27.3	27.9	792	3061
E5 Marple	2.62	39.1	542	8563

Characteristics of Each Dataset

E3 Theia
- Frequent use of general-purpose applications (e.g., *Firefox*, *Thunderbird*)
  → Various command lines are used.

E5 Theia
- Many system administration and update-related processes
  → Usage is concentrated on specific command lines.

E5 Marple
- Many command lines for analyzing document files
  → Usage is concentrated on similar command lines performing the same operations.

E3 Theia: General-purpose system

E5 Theia / Marple: Repetitive, task-specific systems

→ High potential effectiveness for systems that perform repeated, specific operations (e.g., dedicated servers)

Limitations and Future Work

Limitations

- It requires at least partially analyzed data for training.
  → Difficult to apply to environments that have not been analyzed at all.
- Difficult to apply when logs from multiple OSs are mixed, since natural-language features such as command lines and file paths differ by OS.
- The natural language processing component depends on related work(NODLINK).

Future Work

- Optimization of node set size and cosine similarity threshold.
- Verification using a wider variety of datasets.
- Application to intrusion detection systems:
  Extracted benign activities could be utilized in whitelist-based intrusion detection.

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Conclusion

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- Recent studies link and visualize malicious activities for attack analysis.

- The dependency explosion problem remains unsolved.

- We propose a method to reduce dependencies by extracting benign activities using NLP and cosine similarity.

- **Our method demonstrated that:**
  - Dependency reduction through benign activities is feasible.
  - About 10% of system activities can potentially be defined as patterned benign activities.
  - Benign activities can be extracted even from small-scale data (1~3%).

<u>Future Work</u>
- Investigate the effects of parameter variation (node set size, similarity threshold).
- Validate the method using a wider variety of datasets.
- Explore applications to intrusion detection systems.