

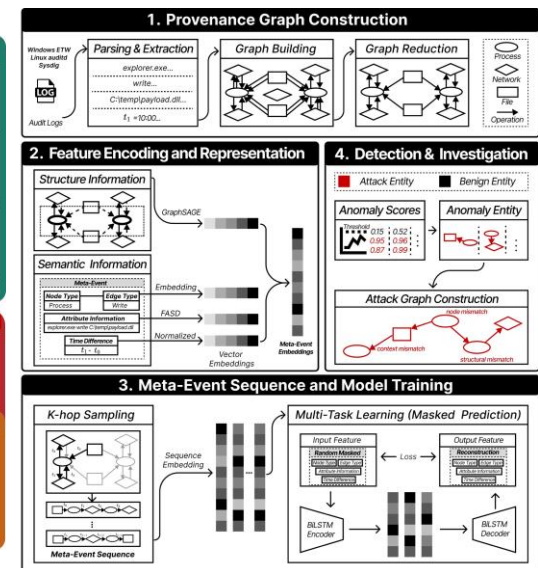
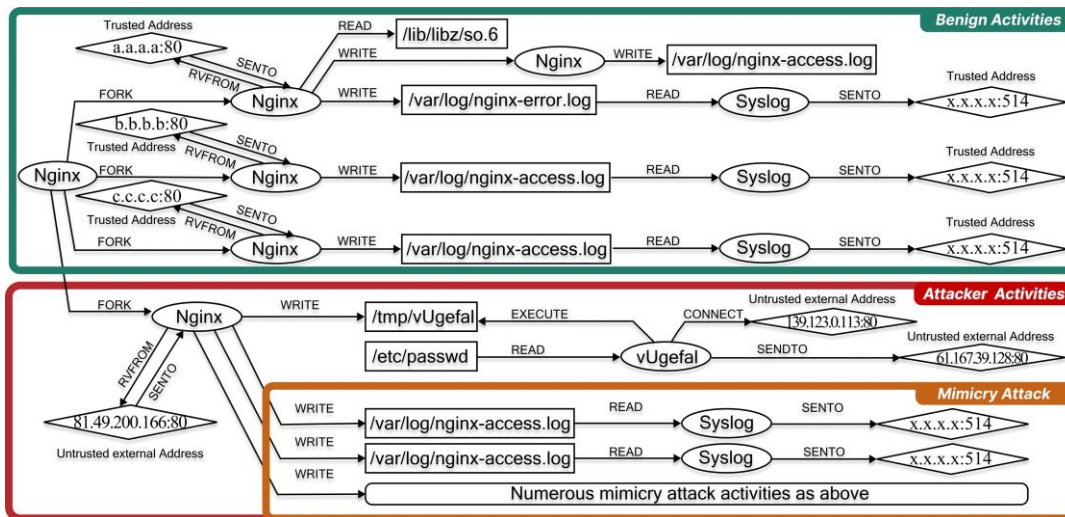
SecGuard: Multi-Dimensional Provenance Analysis for Self- Supervised APT Detection

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Frontiers of Computer Science, DOI: [10.1007/s11704-025-50797-z](https://doi.org/10.1007/s11704-025-50797-z)

Problems & Ideas

- Problems of conventional provenance-based approaches:
 - Vulnerable to mimicry attacks where malicious actions are disguised as benign.
 - Lack fine-grained detection and overlook critical semantic and temporal signals in system audit logs.
- Ideas: A self-supervised framework (SecGuard) that integrates structural, semantic, and temporal features for robust, fine-grained APT detection.



An APT scenario showing malicious (red) and mimicry (orange) activities interwoven with benign behaviors (green), illustrating the detection challenge.

Main Contributions

- Contributions:
 - A novel self-supervised APT detection framework that uniquely integrates structural, semantic, and temporal analysis of provenance graphs.
 - A multi-dimensional approach that provides strong robustness against sophisticated mimicry attacks by making evasion significantly more difficult.
 - Ablation studies confirm that each core component, including our FASD algorithm, is critical for achieving efficient and accurate detection.

Table 1 Performance comparison of SecGuard, ThreaTrace, and FLASH on entity level APT detection across DARPA TC datasets and SimAttack datasets. Pre.: Precision; Rec.: Recall; F1.:F1-score.

Datasets	SecGuard			ThreaTrace [2]			FLASH [4]					
	TP/TN/FP/FN	Pre.	Rec.	F1.	TP/TN/FP/FN	Pre.	Rec.	F1.	TP/TN/FP/FN	Pre.	Rec.	F1.
THEIA (E3)	25 323/3 503 938/1399/28	0.95	0.99	0.97	25 297/3 501 561/3765/65	0.87	0.99	0.93	25 318/3 503 451/1875/44	0.93	0.99	0.96
THEIA (E5)	150 816/8 345 915/38 459/12 019	0.80	0.92	0.85	150 286/8 321 358/63 137/12 428	0.70	0.92	0.80	150 713/8 333 932/50 239/12 325	0.75	0.92	0.83
Trace (E3)	67 361/2 413 301/2727/1	0.96	0.99	0.98	67 382/2 389 233/26 774/1	0.72	0.99	0.83	67 382/2 412 202/3805/1	0.95	0.99	0.97
Trace (E5)	25 091/1 823 599/2453/3520	0.91	0.87	0.89	25 024/1 819 337/6014/4288	0.81	0.85	0.83	25 053/1 820 419/5314/3877	0.83	0.86	0.84
CADETS (E3)	12 812/706 644/358/4	0.97	0.99	0.98	12 848/705 605/1361/4	0.90	0.99	0.95	12 851/706 246/720/1	0.95	0.99	0.97
CADETS (E5)	17 733/478 913/4209/1995	0.81	0.89	0.85	17 685/472 045/10 281/2839	0.63	0.86	0.73	17 694/476 963/5598/2595	0.76	0.87	0.81
SimAttck-1	14 353/695 789/1345/5	0.91	0.99	0.95	14 224/695 021/2229/18	0.86	0.99	0.92	14 249/695 521/1715/7	0.89	0.99	0.94
SimAttck-2	13 183/803 678/1475/27	0.90	0.99	0.94	13 021/802 931/2367/44	0.85	0.99	0.91	13 143/803 437/1752/31	0.88	0.99	0.93

Table 2 Performance comparison of SecGuard, ThreaTrace, Flash, and Unicorn on subgraph-level APT detection across Unicorn dataset scenarios (SC-1, SC-2, and Wget). Pre.: Precision; Rec.: Recall; F1.:F1-score.

Datasets	System	Pre.	Rec.	F1.
Unicorn SC-1 [1]	Unicorn [1]	0.85	0.96	0.90
	Flash [4]	0.92	0.96	0.94
	ThreaTrace [2]	0.93	0.98	0.95
	SecGuard	0.95	0.98	0.97
Unicorn SC-2 [1]	Unicorn	0.75	0.80	0.78
	Flash	0.96	0.96	0.96
	ThreaTrace	0.91	0.96	0.93
	SecGuard	0.93	0.98	0.96
Unicorn Wget [1]	Unicorn	0.86	0.95	0.90
	Flash	0.97	0.93	0.96
	ThreaTrace	0.93	0.98	0.95
	SecGuard	0.97	0.98	0.98

Experimental results show SecGuard consistently outperforms baseline methods on DARPA and Unicorn datasets in both entity-level and subgraph-level detection.