Sometimes Simpler is Better: A Comprehensive Analysis of State-of-the-Art Provenance-based Intrusion Detection Systems

paper

framework

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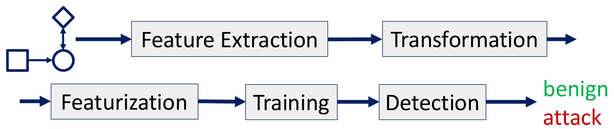
Overview

- We built an **efficient framework** integrating 8 SOTA anomaly-based Provenance-based Intrusion Detection Systems (PIDSs).
- We identified **9 key shortcomings** in their **evaluation** and real-world **applicability**.
- We demonstrate that a **much simpler** neural network outperforms all baselines while **addressing** all 9 shortcomings.

Framework

- A pipeline of 5 restart-able tasks.
- 8 SOTA systems / 9 DARPA datasets.
- 11 encoders / 6 decoders / 9 objectives.
- Integrated hyperparameter tuning.
- Open-sourced



Pipeline comprising 5 tasks, customizable via arguments in YML files

Studied Systems

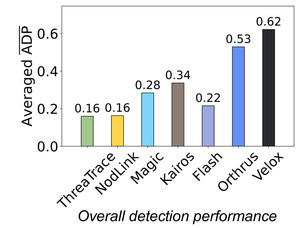
SIGL [1]	USENIX Sec'21
Kairos [2]	IEEE S&P'24
ThreaTrace [3]	IEEE TIFS'22
Flash [4]	IEEE S&P'24
NodLink [5]	NDSS'24
R-Caid [6]	IEEE S&P'24
MAGIC [7]	USENIX Sec'24
Orthrus [8]	USENIX Sec'25

Shortcomings

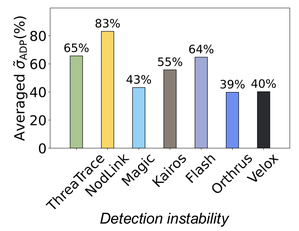
1. **Insufficient Detection Granularity**
   Systems detect at the graph or neighborhood levels, leading to thousands positives to analyze.
2. **Missing Metric to Measure Attack Detection**
   Traditional metrics don't account individual attacks and are biased toward thresholding.
3. **Impractical Thresholding Methods**
   Systems rely on fixed, arbitrary and manually set thresholds that fail to adapt dynamically.
4. **Unfair Comparison with Baselines**
   Evaluation baselines are left untuned, while proposed systems are typically extensively tuned.
5. **Not Measuring Instability**
   The detection performance of systems is extremely instable under identical configurations.
6. **Featurization Methods Trained on Test Data**
   Some systems rely on test data for training, leading to data snooping.
7. **Overly Complex Architectures**
   Systems are usually complex, yet they are rarely compared to much simpler models.
8. **Insufficient Scalability**
   Systems do not meet scalability and overhead requirements for a practical deployment.
9. **Lacking Real-Time Detection**
   Systems are poorly fitted for real-time setting due to their design and overhead.

Key Contributions

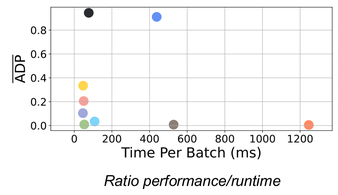
1. We introduce **Attack Detection Precision (ADP)** as a new metric to measure detection capability.
2. We show that all systems have high **detection instability** using relative ADP standard deviation.
3. Systems tend to become more complex, whereas **Velox**, a simple neural network on text features, surprisingly reaches SOTA on 8/9 datasets.



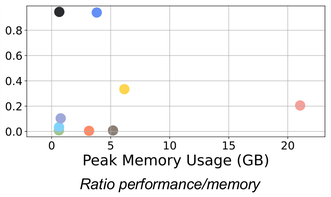
Overall detection performance



Detection instability



Ratio performance/runtime



Ratio performance/memory

Recommendations

- Use fine-grained evaluation methods such as node- or edge-level detection.
- Use cybersecurity-oriented metrics.
- Tune baselines fairly and consistently.
- Evaluate instability through repeated runs.
- Use ablations to find the simplest effective design.
- Ensure scalability and real-time capability.

References

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