Poster: Detecting Anomalous LAN Activities under Differential Privacy

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Abstract

Anomaly detection has emerged as a popular technique for detecting malicious activities in local area networks (LANs). Various aspects of LAN anomaly detection have been widely studied. Nonetheless, the privacy concern about individual users or their relationship in LAN has not been thoroughly explored in the prior work. In some realistic cases, the anomaly detection analysis needs to be carried out by an external party, located outside the LAN. Thus, it is important for the LAN admin to release LAN data to this party in a private way in order to protect privacy of LAN users; at the same time, the released data must also preserve the utility of being able to detect anomalies. This paper investigates the possibility of privately releasing ARP data that can later be used to identify anomalies in LAN. We present four approaches, namely naïve, histogram-based, naïve- δ and histogram-based- δ , and show that they satisfy different levels of differential privacy – a rigorous and provable notion for quantifying privacy loss in a system. Our real-world experimental results confirm practical feasibility of our approaches. With a proper privacy budget, all of our approaches preserve more than 75% utility of detecting anomalies in the released data.

BIBLIOGRAPHIC REFERENCE

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Detecting Anomalous LAN Activities under Differential Privacy

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Motivation

- No prior work so far has explored the privacy implication of performing LAN anomaly detection, especially in many realistic scenarios where the anomaly detection must be performed by an entity outside LAN or third-party software.
- Simply erasing all users' sensitive information from the output data helps with user anonymization. But it does not provide strong and provable privacy guarantees.
- With this simple technique, a motivated adversary may still be able to deanonymize users through other means, e.g., performing a side-channel analysis or correlating the remaining network traces with the physical world data.
- Hence, there is a need for a technique with rigorous privacy guarantees, while preserving the utility of detecting anomalies in the LAN environment.

System Model



Privacy Notions

We choose the LAN privacy notions based on differential privacy – a rigorous and provable notion for quantifying privacy loss in a system. The notions use the ARP-Request degree as their underlying data since it has been shown to be a promising feature for detecting anomalies in LAN.

Let \mathcal{G} be the set of graphs between LAN users. We can define 4 privacy notions in LAN anomaly detection as follows:

Notion 1 ((ϵ, δ)-edge-DP). An algorithm \mathcal{M} : $\mathcal{G} \to \mathcal{Y}$ satisfies (ϵ, δ)-edge-DP if, for every pair of edge-neighboring graphs G and G' and every subset $S \subseteq \mathcal{Y}$,

$$\mathbb{P}\left(\mathcal{M}(G)\in S\right)\leq e^{\epsilon}\mathbb{P}\left(\mathcal{M}(G')\in S\right)+\delta$$

Notion 2 ((ϵ, δ)-node-DP). $\mathcal{M} : \mathcal{G} \to \mathcal{Y}$ satisfies (ϵ, δ)-node-DP if, for every pair of nodeneighboring graphs G and G' and every subset $S \subseteq \mathcal{Y}$,

 $\mathbb{P}\left(\mathcal{M}(G)\in S\right)\leq e^{\epsilon}\mathbb{P}\left(\mathcal{M}(G')\in S\right)+\delta.$

Notion 3 (ϵ -edge-DP). $\mathcal{M} : \mathcal{G} \to \mathcal{Y}$ satisfies (ϵ, δ)-edge-DP if it satisfies ($\epsilon, 0$)-edge-DP.

Notion 4 (ϵ -node-DP). $\mathcal{M} : \mathcal{G} \to \mathcal{Y}$ satisfies (ϵ, δ) -node-DP if it satisfies $(\epsilon, 0)$ -node-DP.

Protection Guarantees

INOUIOII	Ŧ	Protected Info.	Prob.
(ϵ, δ) -edge-DP	1	ARP requests	$1-\delta$
(ϵ, δ) -node-DP	2	LAN users	$1-\delta$
ϵ -edge-DP	3	ARP requests	1
$\epsilon\text{-node-DP}$	4	LAN users	1

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Privacy-preserving algorithms satisfying each notion

Let V_{jk} denote aggregate ARP requests from user k, accumulated at interval j and V_j denote the result after appending all ARP requests of all users generated in interval j. Algorithms satisfying four privacy notions are shown below:

Input: $V = \{V_1, V_2, ..., V_t\}, t, \epsilon, \delta$

Output: $D = \{D_1, D_2, ..., D_t\}$ **Input:** $V = \{V_1, V_2, ..., V_t\}, t, \epsilon$ **Output:** $D = \{D_1, D_2, ..., D_t\}$ $\rho \leftarrow \left(\sqrt{\log\left(1/\delta\right) + \epsilon} - \sqrt{\log\left(1/\delta\right)}\right)^{\frac{1}{2}}$ for j = 1 to t do for j = 1 to t do $D_j \leftarrow \text{SUM}(\text{Degree}(V_j))$ $D_i \leftarrow \text{SUM}(\text{Degree}(V_i))$ $D_j \leftarrow D_j + \text{Laplace}(t/\epsilon)$ $D_j \leftarrow D_j + N(0, t/2\rho)$ if $D_j > 0$ then $D_j \leftarrow int(D_j)$ if $D_j > 0$ then $D_j \leftarrow int(D_j)$ else $D_i \leftarrow 0$ else $D_i \leftarrow 0$ end end Algo 3: Naïve approach satisfying Notion-1 Algo 4: Naïve- δ approach satisfying Notion-2 **Input:** $V = \{V_1, V_2, ..., V_t\}, t, \epsilon, \delta$ **Output:** $D = \{D_1, D_2, ..., D_t\}$ **Input:** $V = \{V_1, V_2, ..., V_t\}, t, \epsilon$ **Output:** $D = \{D_1, D_2, ..., D_t\}$ $\rho \leftarrow \left(\sqrt{\log\left(1/\delta\right) + \epsilon} - \sqrt{\log\left(1/\delta\right)}\right)^{\frac{1}{2}}$ for j = 1 to t do for j = 1 to t do $D_i \leftarrow \text{Histogram}(\text{Degree}(V_i))$ $D_j \leftarrow \text{Histogram}(\text{Degree}(V_i))$ foreach $bin \in D_i$ do foreach $bin \in D_j$ do | $bin.count \leftarrow$ $bin.count \leftarrow$ $bin.count + Laplace(t/\epsilon)$ $bin.count + N(0, t/2\rho)$ if bin.count > 0 then $\begin{array}{l} \textbf{if } bin.count > 0 \textbf{ then} \\ bin.count \leftarrow \operatorname{int}(bin.count) \end{array}$ $bin.count \leftarrow int(bin.count)$ $\mathbf{else} \ bin.count \leftarrow 0$ else $bin.count \leftarrow 0$ end end end Algo 3: Histogram-based approach satisfying Notion-3 end Algo 4: Histogram-based- δ approach satisfying Notion-4

