Wedjat: Detecting Sophisticated Evasion Attacks via Real-time Causal Analysis

Li Gao
Tsinghua University
Beijing, China

Chuanpu Fu
Tsinghua University
Beijing, China

Xinhao Deng
Tsinghua University
Beijing, China

Ke Xu
Tsinghua University
Zhongguancun Lab
Beijing, China

Qi Li
Tsinghua University
Zhongguancun Lab
Beijing, China

Abstract

Traffic encryption has been widely adopted to protect the confidentiality and integrity of Internet traffic. However, attackers can also abuse such mechanism to deliver malicious traffic. Particularly, existing methods detecting encrypted malicious traffic are not robust against evasion attacks that manipulate traffic to obfuscate traffic features. Robust detection against evasion attacks remains an open problem. To the end, we develop Wedjat, which utilizes a causal network to model benign packet interactions among relevant flows, such that it recognizes abnormal causality that represents malicious traffic and disrupted causality incurred by evasion attacks. We extensively evaluate Wedjat with millions of flows collected from a real-world enterprise. The experimental results demonstrate that Wedjat achieves an accuracy of 0.957 F1-score when detecting various advanced attacks. Notably, five sophisticated evasion attacks, which have successfully evaded all existing methods, are accurately detected by Wedjat with over 0.915 F1. It demonstrates that Wedjat achieves exceptional robustness against evasions. Meanwhile, Wedjat maintains an outstanding detection latency, i.e., it can predict each packet in less than 0.125 seconds.

CCS Concepts

• **Security and privacy → Intrusion detection systems**.

Keywords

Machine learning; malicious traffic detection systems; deep learning; causal network

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1 Introduction

Traffic encryption protects the confidentiality and integrity of communications by concealing private data in encrypted packets. Currently, over 98% of Internet users enable traffic encryption, such as Transport Layer Security (TLS) [37], which thwarts traffic surveillance along routing paths [15]. However, attackers can also abuse traffic encryption to conceal their malicious activities [12], e.g., data breach [52], malware delivery [51], and vulnerability exploiting [41]. Existing study [12] shows that over 70% of network attacks are launched through encrypted traffic. Traffic encryption can easily invalidate traditional Deep Packet Inspection (DPI) that detects attacks by inspecting packet payloads [40, 43, 49, 57, 59].

To mitigate such threats, machine learning (ML) based malicious traffic detection systems have been developed [20, 21, 23, 32, 38, 59], which capture stealthy malicious traffic by learning traffic features, for instance, the number of bytes in transferred packets. Powered by advanced flow features extracted from sequences of packets [7, 20, 47], existing detection systems can capture stealthy attacks constructed by encrypted traffic [3, 12] other than plain-text traffic to complement traditional rule-based detection [49, 57, 59].

Unfortunately, existing methods for encrypted traffic detection [12, 20, 21, 23, 30] are not robust against evasion attacks [1, 8, 13, 22, 26, 36, 48]. Specifically, attackers construct adversarial examples by injecting perturbations into attack flows, for example, through inserting dummy packets, padding packets, and delaying packets[13, 19, 36]. Thus, attackers can easily evade existing detection systems that heavily rely on coarse-grained flow-level features [7, 23, 31, 38]. In particular, sophisticated evasion attacks simultaneously manipulate features of many concurrent malicious flows, resulting in significant decreases in detection accuracy [3, 7, 13, 20, 21, 48].

To this end, we set out to develop a robust detection system for detecting encrypted malicious traffic, which is robust against various evasion strategies. We observe that evasion behaviors, which manipulate traffic features, such as adding or delaying packets, violate packet interactions regulated by network protocols and original traffic behaviors. Thus, we can capture such anomalies by modeling benign packet interaction patterns of relevant flows as between-flow causality, and recognize abnormal packet interactions that deviate from the benign patterns as the violation of the causality, which are treated as malicious traffic, including that constructed by evasion attacks.

In this paper, we develop Wedjat, a malicious traffic detection system that utilizes a casual network to model packet interaction patterns between massive real-world users. It can capture various encrypted malicious traffic that deviates from the benign interaction and different evading variants that violate normal behavior patterns. Moreover, by utilizing interactions between different and relevant flows, Wedjat is robust against flow-level, packet-level, and multi-flow evasion attacks. Since evasion attacks manipulate coarse-grained traffic features [7, 38, 59, 61], which inevitably exhibits abnormal interaction patterns, allowing Wedjat to recognize

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Table 1: The comparison with the existing methods of malicious traffic detection.

Categories	Model	Traffic Feature	Detection Granularity	Typical Method	Detection Ability: Encrypted Traffic	Detection Ability: Unseen Traffic	Detection Ability: Realtime Detection	Detection Robustness: Packet-Level	Detection Robustness: Flow-Level	Detection Robustness: Multi-Flow
Fixed-Rule	w/o	Payloads	Packet	Zeek [57]	×	×	×	×	×	×
	w/o	Flow Features	Flow	Poseidon [59]	×	×	×	×	×	×
Machine Learning	AutoML	Packet Binaries	Packet	nPrintML [23]	✓	×	✓	×	×	×
	Auto Encoders	Packet Statistics	Packet	Kitsune [38]	×	×	✓	×	×	×
	RNNs	Packet Byte segments	Flow	EBSNN [54]	✓	×	×	×	×	×
	Random Forest	Packet Distributions	Flow	FlowLens [7]	×	×	✓	×	×	×
	K-Means	Flow Frequency Features	Flow	Whisper [20]	✓	✓	✓	×	✓	×
	RNNs	Packet Length Sequence	Flow	FS-Net [31]	✓	✓	×	×	✓	×
	Transformers	Raw Data Trace	Flow/Packet	ET-bert [30]	✓	✓	✓	×	✓	×
	Graph	Host Interactions	Flow	HyperVision [21]	×	✓	✓	✓	✓	×
	SVM	Multi-Flow Statistics	Multi-Flow	Invariant Bag [8]	×	✓	×	✓	✓	×
	Causality	Packet Interactions	Flow/Packet	Wedjat	✓	✓	✓	✓	✓	✓

such patterns as significant violations of the causality and thus capture evading malicious traffic.

Note that, it is non-trivial to model complex packet interaction patterns among various encrypted packets with different encryption protocols on the Internet. First, Internet packets are unstructured data, which are generated by many different encryption protocols [12, 37]. This necessitates a generic packet embedding method independent of encryption protocols. Second, due to the large scale of Internet traffic behaviors, users exhibit complex interaction patterns that existing ML models find impossible to learn, especially the between-flow relationships of traffic. Last, interactions between multiple flows may incur high detection latency, making it difficult to realize real-time detection.

To address these challenges, we model the relationship among encrypted packets as a causal network that represents the semantics of application layer protocols (e.g., HTTPS and SMTP). However, evasion behaviors, which manipulate traffic features such as padding dummy packets [19], violate the semantics of the protocol. Therefore, Wedjat effectively detects malicious packets by investigating the causality among packets. Specifically, we develop a packet embedding method that clusters fine-grained packet-level features. In this way, Wedjat can effectively convert unstructured Internet packet data into numerical representations. Moreover, Wedjat utilizes a causal network, a probabilistic graph model, to model interactions of packets in relevant flows. Finally, it utilizes belief propagation to infer the most probable next behavior in real-time to detect attacks, in particular, the stealthy attacks that are generated by evasion behaviors. Moreover, the sparse casual network avoids intensive computation and can boost real-time detection.

We extensively evaluate Wedjat in a top-ranked network infrastructure provider. Specifically, we collected 13 million flows from real enterprise networks including malicious traffic associated with real-world threats. The experimental results demonstrate that Wedjat can capture various unseen attacks with an accuracy of 0.9577 F1-score, thereby outperforming the five stat-of-the-art methods. In particular, five evasion attacks, which can easily evade all existing malicious traffic detection [3, 8, 20, 21, 31, 38], are accurately captured by Wedjat with over 0.9158 F1-score. Meanwhile, Wedjat significantly improves the accuracy over existing methods on existing traffic datasets. Besides, Wedjat can realize real-time detection, with its detection latency bounded by 0.125s.

The contributions of this paper are five-fold:

- We develop the first robust encrypted malicious traffic detection system that utilizes the casual network model to detect sophisticated and strategic evasion attacks by analyzing between-flow interaction patterns.
- We design a packet embedding method that effectively converts unstructured packets into numerical representations.
- We innovatively utilize the causality to model the complex packet interactions among various encrypted flows for traffic analysis.
- We devise a real-time inference-based detection process for efficient classification of ongoing connections.
- We deploy Wedjat in a large-scale real-world enterprise to extensively evaluate its performance.

The rest of this paper is organized as follows: In Section 2, we formulate the problem. In section 3, we present the motivation and high-level design of Wedjat. In Section 4, we present design details. In Section 5, we experimentally evaluate Wedjat. Section 6 reviews related works, and Section 7 concludes this paper.

2 Problem Statement

2.1 Design Goals

Wedjat aims to identify encrypted traffic generated by various Internet attacks, in particular the malicious traffic generated by evasion attacks. For instance, existing malware commonly uses TLS traffic encryption protocols to communicate with botmasters [4, 28], because encrypted packet payloads can evade traditional NIDSes that rely on plain-text packet payloads. Therefore, Wedjat only analyzes the features of ongoing Internet traffic at the gateway of a network. In addition, Wedjat should capture unseen zero-day attacks [38, 50], which means that it cannot obtain any prior knowledge of the attacks, e.g., labeled datasets for training ML models. Moreover, it should realize generic detection to capture various advanced attack traffic [15, 27], regardless of their speeds, durations, and protocols. Besides, Wedjat should achieve real-time detection, which allows existing defense systems to throttle attack traffic in real time [34, 59].

In particular, we aim to develop robust detection against evasion attacks. Specifically, existing evasion attacks inject perturbations to manipulate traffic features, for example, through injecting and

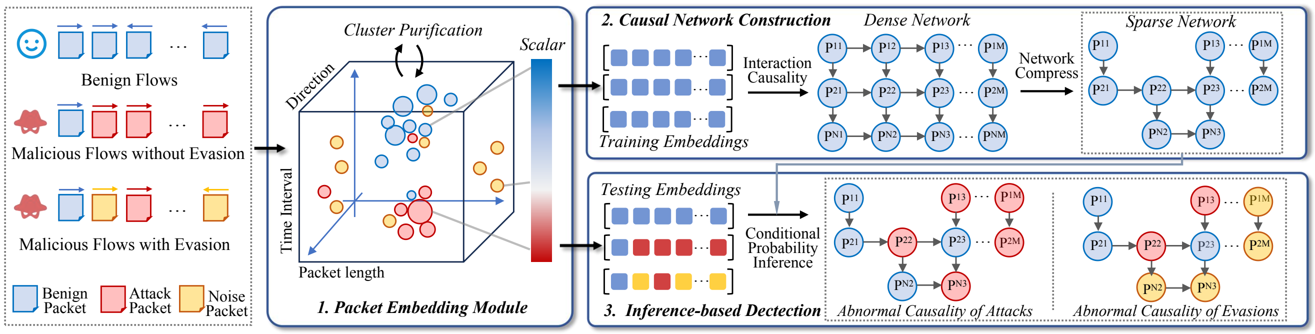


Figure 1: The overview of Wedjat.

revising benign packets. Moreover, unlike existing studies that focus on specific evasion attacks [19, 20], we consider various evasion attacks, particularly, those sophisticated attacks that manipulate the features of many flows. In general, existing evasion attacks can be categorized into three classes:

- *Packet-Level Evasion.* Attacker add noise to the feature of one packet, e.g., through padding, delaying, and inserting packets [36], which can easily evade existing packet-level detection [23, 38, 61].
- *Flow-Level Evasion.* Attackers obfuscate features of flows (e.g., the flow completion time[7], flow length and duration[22] and the number of bursts [1, 26]), by manipulating features of multiple packets within one single flow [20].
- *Multi-Flow Evasion.* Attackers manipulate massive correlated malicious flows, for example, by inserting benign flow among malicious flows [21] and inject perturbations to many concurrent malicious flows simultaneously [22].

Note that, the adversarial flow examples constructed by these evasion attacks can easily evade many existing detection [7, 20, 21, 38, 47]. Since attackers can easily manipulate the coarse-grained statistical traffic features utilized by these methods.

2.2 Problem Formulation

This paper focuses on addressing evasion attacks that will result in the *target distribution* of testing samples being different from the *source distribution* of training samples. Evasion attacks inject perturbations to construct adversarial traffic examples, which introduces drift in the distribution of traffic features. Specifically, let $D_S = D_S^+ \cup D_S^- := \{(\boldsymbol{x}^{S,i}, y^{S,i})\}_i^{n_S}$ denote a labeled dataset which obeys the source distribution $\mathbb{P}_S$, where $n_S = |D_S|$ is the scale of the dataset. Note that, $D_S^+ = \{(\boldsymbol{x}^S, +)\}$ and $D_S^- = \{(\boldsymbol{x}^S, -)\}$ respectively represent the dataset of benign samples from distribution $\mathbb{P}_S^+$ and malicious samples from $\mathbb{P}_S^-$. Meanwhile, $y^i \in \mathscr{Y} = \{+, -\}$ where label $+$ and $-$ indicate benign and malicious respectively. In the detecting phase, given an unlabeled dataset $D_T = D_T^+ \cup D_T^- := \{(\boldsymbol{x}^{T,i}, \cdot)\}_i^{n_T}$ sampled from the distribution $\mathbb{P}_T$, our objective is to utilize training dataset D_S to construct a ML model $f(\cdot)$ and predict the associated label of the any feature vector $\boldsymbol{x}^T \in D^T$. We denote the output label of sample $\boldsymbol{x}$ as $\hat{y} = f(\boldsymbol{x})$. From a probabilistic perspective, the process of prediction is to compute $P(y|\boldsymbol{x})$ and can be described as:

$$\hat{y} = \underset{y \in \{+,-\}}{\arg\max} P(y|\boldsymbol{x}; D_S) \quad \forall \boldsymbol{x} \in D_T \tag{1}$$

However, the target distribution of malicious data $\mathbb{P}_T^-$ exhibits various changes compared to the source distribution $\mathbb{P}_S^-$, which is caused by evasion attacks described as $E(\cdot)$. The serious phenomenon $\mathbb{P}_T^- := \mathbb{P}_{E(S)}^- \neq \mathbb{P}_S^-$ is unknown to detector. Additionally, for benign traffic, $\mathbb{P}_T^+$ is similar to $\mathbb{P}_S^+$. Evasion can lead to misclassification. For example, given a malicious flow $\boldsymbol{a}$ labeled with $-$, $f(\boldsymbol{a}) = -$ but $f(E(\boldsymbol{a})) = +$ will happen simultaneously, which leads to poor robustness. This is because, evasion attacks make $\boldsymbol{a}$ be similar to a benign sample, which can be defined as $P(E(\boldsymbol{a})|-) < P(E(\boldsymbol{a})|+)$. According to the Bayesian formula and the Full Probability formula $P(y|E(\boldsymbol{a})) \propto P(E(\boldsymbol{a})|y)P(y)$, hence $P(-|E(\boldsymbol{a})) < P(+|E(\boldsymbol{a}))$ and then $\hat{y} \rightarrow +$.

3 Overview of Wedjat

3.1 Design Intuition

The evasion behaviors of attack traffic, which can easily manipulate traditional statistical traffic features (e.g., the number of packets), exhibit abnormal packet interactions that deviate from the normal interactions as regulated by behaviors and network protocols [15, 27, 37]. However, we observe that interactions of benign and malicious traffic have distinct patterns. In particular, between-flow pattern of malicious flows (even with evasion behaviors) are distinct from that of benign flows[1]. Thus, we can use between-flow and within-flow patterns to detect different evasion behaviors. To achieve this, we leverage causality analysis based on the probabilistic graph model to model packet interactions among Internet users and recognize the violations of the causality which represent abnormal packet interactions associated with evasion behaviors and attack behaviors. To effectively model packet interactions among users, we define the causality between packets as below:

Definition 1. *Causality refers to the dependency relationship between variables. If the value or occurrence of the variable X may influence the variable Y, we call this relationship as causality, denoted as $X \implies Y$. Causality can be quantified by the conditional probability $P(Y|X)$, where $P(Y|X) \neq P(Y)$ indicates that the occurrence of Y is dependent on the occurrence of X.*

In this paper, we use within-flow causality to denote the probabilistic dependency among packets from one flow and use between-flow causality to indicate that among the packets from different flows.

[1]Detailed analysis can be found in Appendix C.

3.2 High-Level Design

We develop Wedjat, which captures evasion attacks by analyzing fine-grained packet interactions via real-time causality analysis. As shown in Figure 1. In general, Wedjat models causal relationships between packets and flows. That is, the nodes in the causal network represent packets, while the edges represent conditional probabilities between packets. Based on common benign causal patterns, Wedjat utilizes known packets to infer unknown packets, thereby identifying abnormal causality that indicates malicious traffic and evading traffic detection. In specific, Wedjat includes three modules:

Packet Embedding. We convert unstructured packets generated by various encryption protocols into unified numerical representations. That is, we extract packet-level features and embed the features into one single dimension, which serves as the input for causality analysis. Meanwhile, we ensure that such numerical representations can differentiate malicious packets. For this purpose, we formulate an optimization problem upon the clusters of packet features to purify the clusters and to score the clusters as either benign or malicious. Subsequently, we calculate the similarity between each packet and the associated cluster. Finally, we produce the numerical representation for each packet by combining the score and similarity of the associated cluster.

Causal Network Construction. We model causality among packets of related flows from the same sources and destinations. Specifically, we develop a causal network based on a Directed Acyclic Graph (DAG), where one node denotes one packet and the edges denote the probabilistic dependencies between nodes. Particularly, to reduce the complexity of inter-flow dependency between massive packets, we design a network construction based on the semantics of network protocols and optimize the network structure to compress redundant network nodes and edges for efficient detection. Note that, the learning process does not rely on labeled malicious traffic, thereby realizing detection for many unseen attacks.

Inference-based Detection. In this module, we recognize the deviations of the causality which denote the abnormal interactions exhibited by malicious and evasion behaviors. To accurately detect abnormal interaction patterns, we develop two-step detection methods that capture coarse-grained flow-level abnormal interactions based on fine-grained packet-level anomalies. Initially, we derive the scores that indicate malicious degree from the packet embedding module. Afterward, we compare the packet score with the inference result provided by the causal network. In this way, we effectively capture ongoing abnormal behaviors in real-time.

4 Design Details

4.1 Packet Embedding

In order to characterize unstructured packets from different protocols, we extract numerical information of arriving packets and compress them to a numerical value for future network construction. The principle of mapping is to differentiate between normal and malicious packets, as well as identify outliers representing unseen packets. The mapped results should represent the benign degree of packets. Hence, our objective can be written as a function named $Map : \mathbb{R}^d \to [-1, 1]$, and $\boldsymbol{p} \mapsto score_{\boldsymbol{p}}$. For $score_{\boldsymbol{p}}$, we assign benign, malicious and unknown packet to the interval $[\epsilon, 1]$,$[-1, \epsilon]$ and $[-\epsilon, \epsilon]$ respectively, where ϵ is a hyperparameter range from $0 < \epsilon < 0.5$ referring to the threshold whether it is an unknown packet.

$$
score_{\boldsymbol{p}} = M(\boldsymbol{p}) \in
\begin{cases}
(\epsilon, +1] \,, & \text{if } \boldsymbol{p} \in D^{+}_{\boldsymbol{p}} \text{ ,i.e., } P(\hat{y} = + | \boldsymbol{p}) > 0.5 + \varepsilon \\
[-\epsilon, \epsilon] \,, & \text{if } \boldsymbol{p} \in D^{0}_{\boldsymbol{p}} \text{ ,i.e., } |P(\hat{y} = + | \boldsymbol{p}) - 0.5| \le \epsilon \\
[-1, -\epsilon) \,, & \text{if } \boldsymbol{p} \in D^{-}_{\boldsymbol{p}} \text{ ,i.e., } P(\hat{y} = + | \boldsymbol{p}) < 0.5 - \varepsilon
\end{cases} \tag{2}
$$

Packet Embedding is divided into four steps.

Feature Extraction. We first extract a training packet dataset $D_{S_{\boldsymbol{p}}} = \{(\boldsymbol{p}^{S,i}, y^{S,i})\}_i^{n_{S_{\boldsymbol{p}}}}$ from training flow dataset D_S, where $\boldsymbol{p}^{S,i} \in \mathbb{R}^d$ refers to the i-th packet sample in $D_{S_{\boldsymbol{p}}}$ and $y^{S,i} \in \mathscr{Y}$ refers to the corresponding label, which depends on the label of the flow to which the packet belongs. For each packet, we extract side-channel information in its header segment, e.g., packet length, time-interval, packet direction and so forth. Hence, each packet can be represented as a d-dimensional vector:

$$
\boldsymbol{p}^i = (p^i_1, p^i_2, \ldots, p^i_d) \tag{3}
$$

Normalization is applied to all packet vectors.

$$
\begin{aligned}
\tilde{\boldsymbol{p}}^{S,i} &= (\tilde{p}^{S,i}_1, \tilde{p}^{S,i}_2, \ldots, \tilde{p}^{S,i}_l, \ldots, \tilde{p}^{S,i}_d) \\
\tilde{p}^{S,i}_l &= \frac{p^{S,i}_l - \min_i(p^{S,i}_l)}{\max_i(p^{S,i}_l) - \min_i(p^{S,i}_l)}, \quad i \in [1, n_{S_{\boldsymbol{p}}}]
\end{aligned} \tag{4}
$$

Clustering. To map the d-dimensional vector of each packet to a one-dimensional value, we apply Clustering to the training dataset $D_{S_{\boldsymbol{p}}}$. The objective of kmeans clustering is to partition the dataset into N_c non-overlapping clusters $\mathscr{C} = \{C_1, C_2, ..., C_{N_c}\}$, where N_c is the predetermined number of clusters. The algorithm is to optimize the following cost function:

$$
\mathscr{C}^* = \arg\min_{\mathscr{C}} \sum_{i=1}^{N_c} \frac{1}{|C_i|} \sum_{k,j \in C_i} d(\boldsymbol{p}^k, \boldsymbol{p}^j) \tag{5}
$$

where $d(\cdot,\cdot)$ is the Euclidean distance function. The optimization solving details are provided in the appendix A.1.

Purification. In order to better distinguish the benign packets and malicious packets, namely purify these clusters, there are a variable ${N_c}^*$ that need to be further determined. Therefore, we minimize the following objective function (6), measuring the distance between clustering results and ground truth:

$$
\begin{aligned}
{N_c}^*, \mathscr{C}^* &= \arg\max_{N_c, \mathscr{C}} \sum_{C_j \in \mathscr{C}} \left| P(y = + | C_j) - BenignScore_{C_j} \right| \\
BenignScore_{C_j} &= \begin{cases}
1, & \textbf{if} \quad P(y = + | C_j) > 0.5 + \epsilon \\
0.5, & \textbf{if} \quad \left| P(y = + | C_j) - 0.5 \right| < \epsilon \\
0, & \textbf{if} \quad P(y = + | C_j) < 0.5 - \epsilon
\end{cases}
\end{aligned} \tag{6}
$$

where $P(y = + | C_j) = \frac{Cnt(y^i = +)}{Cnt(p^i \in C_j)}$ denotes the benign probability of each cluster, i.e., the portion of benign labels in each cluster. Details are in Appendix B.

Packet Score. The last step of packet embedding is to set the value of packet points to construct nodes for the causal network. We firstly compute the similarity of a given data point with respect to its belonging cluster's C_j, namely, the distance between the data and the cluster center it belongs to:

$$sim(\boldsymbol{p}^i; C_j) = \frac{1}{|C_j|} \sum_{k \in C_j} d(\boldsymbol{p}^i, \boldsymbol{p}^k), \quad \boldsymbol{p}^i \in C_j \tag{7}$$

We set a threshold τ_{out}: if $sim(\boldsymbol{p}^i; C_j) < \tau_{out}$, we denote this packet as a outlier point.

Moreover, the packet's score can be computed as below equation:

$$score(\boldsymbol{p}^i) = sim(\boldsymbol{p}^i; C_j) \cdot [2 \times P(+|C_j) - 1] \tag{8}$$

Note that $[2 \times P(+|C_j) - 1]$ maps the benign probability interval $[0, 1]$ to the score interval $[-1, 1]$. Hence, the score of packets from benign flows is near to 1, the score of packets from malicious flows is near to -1 and the score of packets from unknown flows is near to 0. The equation of our packet mapping module (2) is satisfied.

Note that the scores of packets are all continuous variables and it may cause large complexity in the learning phase, so we discretize them through the equal-width discretization method by dividing an interval into equal parts. The smaller the partition size, the closer to the original data distribution characteristics but the larger the number of parameters.

4.2 Causal Network Construction

Our causal network involves nodes, edges, structure learning, and parameter learning. We use the following three steps to construct a causal network.

Bag Aggregation. The between-flow relationship brings about notable information that can differentiate normal and malicious traffic. Hence, we first aggregate flows from identical source IP and destination IP pairs to bags of size $N \times M$ in preparation for network construction. For nodes and edges, each node $Node_{i,j}$ represents a packet $\boldsymbol{p}_{i,j}$, namely, the j-th packet in the i-th flow of the bag. Each directed edge represents a causality between the parent node and the child node. The values of nodes are the numerical representation of packets preliminarily obtained in equation 8 in Packet Embedding. The parameters of these edges denote the conditional probability of two nodes.

Fundamental Causal Network. We devise a fundamental causal network because packets exhibit causality in both temporal order and spatial location. For each node $Node_{i,j}$, we establish edges as follows: $Node_{i,j} \Rightarrow Node_{i-1,j}$ and $Node_{i,j-1} \Rightarrow Node_{i,j}$. In the special case where i equals 1, only one edge, $Node_{i,j} \Rightarrow Node_{i-1,j}$, is constructed. Similarly, the same condition applies when $j = 1$ is the case. Therefore, this constitutes a dynamic programming process, and the algorithm details are in appendix 2.

Structure and Parameters Learning. In this process, we optimize the network structure to obtain the maximum likelihood score via randomly deleting edges from the fundamental network[10], thus improving the inference speed. The computation of the maximum likelihood score is also called parameter learning, which learns the joint probability distribution of the causal network. We use the Maximum Likelihood Estimation(MLE) method to estimate network parameters, which can be described as:

$$\begin{gathered} \theta^* = \arg\max_{\theta} lnL(\theta; D_S^+) \\ L(\theta; D_S^+) = \prod_{k=1}^{|D_S^+|} P(\boldsymbol{x}^{S,k}; \theta) \end{gathered} \tag{9}$$

where $\boldsymbol{x}^{S,k} = \boldsymbol{b}^{S,k} = \{\boldsymbol{p}_{11}^{S,k}, \boldsymbol{p}_{12}^{S,k}, ..., \boldsymbol{p}_{nm}^{S,k}\}$, representing the k-th sample, i.e., bag, in the dataset D_S^+. Each $\boldsymbol{x}^{S,k}$ contains N flows and M packets in each flow. The equation (9) above can be reformulated as follows:

$$\begin{aligned} L(\theta; D_S^+) &= \prod_{k=1}^{|D_S^+|} P(\boldsymbol{p}_{11}^{S,k}, \boldsymbol{p}_{12}^{S,k}, ..., \boldsymbol{p}_{NM}^{S,k}; \theta) \\ &= \prod_{k=1}^{|D_S^+|} \prod_{i=1}^{N} \prod_{j=1}^{M} P(\boldsymbol{p}_{ij}^{S,k} | parent(\boldsymbol{p}_{ij}^{S,k})) \\ &= \prod_{k=1}^{|D_S^+|} P(\boldsymbol{p}_{11}^{S,k}) \prod_{k=1}^{|D_S^+|} \prod_{i=2}^{N} P(\boldsymbol{p}_{i,1}^{S,k} | \boldsymbol{p}_{i-1,1}^{S,k}) \prod_{k=1}^{|D_S^+|} \prod_{j=2}^{M} P(\boldsymbol{p}_{1,j}^{S,k} | \boldsymbol{p}_{1,j-1}^{S,k}) \\ &\cdot \prod_{k=1}^{|D_S^+|} \prod_{i=2}^{N} \prod_{j=2}^{M} P(\boldsymbol{p}_{i,j}^{S,k} | \boldsymbol{p}_{i-1,j}^{S,k}, \boldsymbol{p}_{i,j-1}^{S,k}) \end{aligned} \tag{10}$$

Optimal parameters θ are obtained by computing the derivative of the log form of Eq. (10) and setting it equal to zero. Note that, the learning process only involves training benign samples because we only learn the invariant causality from benign traffic.

In general, it is challenging to model relationships among packets across multiple flows because of the vast scale of Internet packets. For example, N concurrent flows, each containing M packets, will incur a complexity of $O(MN*MN)$. Wedjat addresses this challenge by compressing the causality network to effectively model the complex interactions.

4.3 Inference-based Detection

We design a unique packet label inference mechanism that aims to use the inference algorithm to predict the score of the next packet based on the arrived packet and the network structure parameters. In the case where the difference between the predicted score and the newly arrived packet obtained by the mapping mechanism is greater than the setting threshold τ_p, it is considered that the packet does not conform to the pattern of benign traffic. If the number of such situations in traffic is greater than a certain threshold τ_f, the entire traffic is malicious.

Packet Label Inference. Upon the arrival of each data packet, the discrepancy between its observed value and the predicted value is computed. If this discrepancy surpasses a predefined threshold, the packet is classified as a Malicious packet.

The observed value is the score obtained through Packet Embedding, i.e., the probability that a packet is indeed benign: $score_i = P(y = +|\boldsymbol{p}) = M(\boldsymbol{p})$. We use the belief propagation algorithm[10] to calculate:

$$score^*_{\boldsymbol{p}_{i,j}} = \arg\max_{score} P(\boldsymbol{p}_{i,j} = score | \boldsymbol{p}_{1,1}, \ldots, \boldsymbol{p}_{i-1,j-1}) \tag{11}$$

if $|score_{\boldsymbol{p}_{i,j}} - score^*_{\boldsymbol{p}_{i,j}}| > \tau_p$, this packet is abnormal.

Flow Label Inference. For each flow label, we compute the proportion of anomalous packets in a single flow, namely, Flow-wise

Inference Accuracy(FIA).

$$FIA(\boldsymbol{f}_i; M) = \frac{1}{M}\sum_{j}^{M} I(|score_{\boldsymbol{p}_{i,j}} - score^*_{\boldsymbol{p}_{i,j}}| > \tau_p) \tag{12}$$

where $I(\cdot)$ is an indicator function that takes the value 1 when the condition is satisfied. If the FIA of each flow is greater than a certain threshold τ_f, the entire traffic is malicious. For ongoing traffic, we obtain the real-time label through computing $FIA(\boldsymbol{f}_i; l)$ under the sequence of packets up to the current latest packet $\boldsymbol{p}_{i,l}$.

5 Experimental Evaluation

5.1 Experiment Setup

Implementation. We prototype our method with more than 5,000 lines of code[2]. Specifically, we utilize the Python with DPKT library to parse PCAP packet files and to assemble them into flows and bags based on their five-tuple. More precisely, the constructed datasets comprise packet labels and features (e.g., packet lengths, timestamps, directions, etc.), which are saved in JSON format and stored with MongoDB. We set $N = 3$ and $M = 10$ by default, which trades off between accuracy and efficiency.

Datasets. To extensively evaluate Wedjat, we collaborate with a top-ranked network infrastructure provider and use real-world datasets for evaluation. Currently, Wedjat is deployed as an offline attack investigation tool in a Security Operations Center (SOC) [2], which analyzes encrypted traffic collected from the gateway of an enterprise network. We validated our results of Wedjat by using 21-day real-world datasets. Wedjat is utilized to capture all malicious flows, which enables identifying vulnerabilities and performing comprehensive forensic analysis in real time.

Specifically, the large-scale dataset from enterprise networks consists of 735,997 TLS-encrypted malicious flows and 12,436,861 benign encrypted flows. We randomly select 100,000 bags of malicious and benign flow evenly. More precisely, the set of bags comprises 122,073 benign flows and 134,456 malicious flows, respectively. Meanwhile, we utilize existing public datasets, i.e., CICIDS-2017 [44], to complement the real-world datasets, thereby validating the results and avoiding the issue of dataset bias. Such dataset covers traffic of 12 different attacks, e.g., malware traffic, flooding traffic, and botnet traffic. Similarly, we evenly select benign and malicious flows that make up 1,404 and 1,627 bags of traffic. Figure 2 plots the distributions of packet length and direction. Note that, we randomly split the 20% of the whole dataset as a testing set, while the remaining 80% samples are used as the training set. Note that, the labels are only used as ground truth, to calculate detection accuracy. Wedjat does not use labels for training the causal model.

Baselines. We compare Wedjat with five state-of-the-art malicious traffic detection methods. These baselines utilize various features and ML models, covering both supervised [3] and unsupervised [19] methods, flow [31] and packet [38] based methods, single-flow [31] and multi-flow [21] based methods.

- **Kitsune.** Kitsune [38] employs autoencoders to learn statistics of packet-level features, which utilize unsupervised ML to capture various unseen attacks.

[2]The source code of *Wedjat* is available at: https://anonymous.4open.science/r/Wedjat

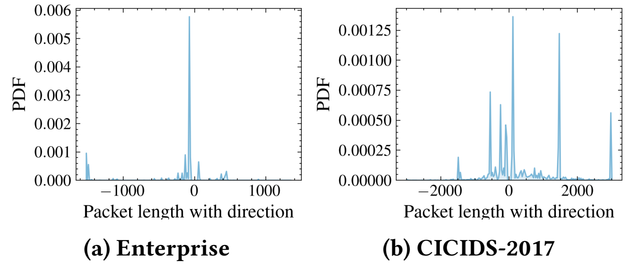


Figure 2: Probability density functions of packet length with direction.

- **Enhanced + SVM.** Anderson *et al.* [3] developed an enhanced feature set for encrypted traffic detection, which consists of a Markov chain transformation and statistics, e.g., minimum and mean of packet lengths. For end-to-end detection, we apply a Support Vector Machine(SVM) model to learn these features.
- **FS-Net.** FS-Net [31] is a deep learning-based method that leverages multi-layer bidirectional gated recurrent units (Bi-GRUs) to capture abnormal sequential features from packet length sequences for traffic detection.
- **Whisper.** Whisper [20] utilizes K-Means to cluster the frequencies of packet-level features, thereby identifying outlier samples as malicious traffic.
- **Hypervision.** Hypervision [21] utilizes a graph to represent interaction patterns among hosts. It detects abnormal interaction patterns by analyzing the statistics of graph structural features.

We emphasize that Wedjat is an unsupervised approach; thus, we focus on comparing unsupervised baselines, including existing robust detection against single-flow evasions [19, 21]. These methods heavily rely on statistical traffic features, which are not robust against evasion attacks.

Selected Evasion Attacks. We simulated five evasion attacks, including Random Delaying, Random Padding, FRONT [22], WTF-PAD [26], and DFD [1]. Note that, the last three evasion strategies are injection-based methods.

- **Random Delaying.** It randomly chooses and delays original packets by randomly generating a millisecond-level delay time.
- **Random Padding.** It pads a random amount of data to packet payloads under the restriction that the packet size is less than the Maximum Transmission Unit (MTU).
- **FRONT.** FRONT[22] injects multiple packets at the stage of flow establishment to obscure the most distinguishable features. It sets injection times to follow a Rayleigh distribution.
- **WTFPAD.** WTFPAD[26] injects packets at sparse gaps in flow to prevent long gaps from becoming distinguishing features.
- **DFD.** DFD[1] injects dummy messages into every outgoing burst with a certain disturbance rate to obfuscate burst patterns.

These evasion attacks indicate that existing systems are vulnerable to simple evasion strategies, such as injecting benign packets for effectively obfuscating flow patterns. In the experiment, we measure performance degradation caused by evasion attacks with different overheads, i.e., delaying time intervals and amount of injected data. Specifically, *time overhead* is defined as the proportion of total delaying time to the original flow completion time, and *data*

Table 2: Accuracy comparison without evasion attacks.

Dataset	Method	Non-Evasion Scenario		
		Pre	Rec	F1
Enterprise	Kitsune	0.9223	0.7913	0.8518
	Enhanced+SVM	0.8864	0.9896	0.9352
	FS-Net	0.9830	0.9798	0.9814
	Whisper	0.9323	0.9117	0.9219
	Hypervision	0.9170	0.9632	0.9395
	Wedjat	**0.9387**	**0.9775**	**0.9577**
CICIDS-2017	Kitsune	0.9524	0.9016	0.9263
	Enhanced+SVM	0.7128	0.8316	0.7676
	FS-Net	0.9865	0.9816	0.9841
	Whisper	0.9180	0.9516	0.9345
	Hypervision	0.9624	0.9833	0.9727
	Wedjat	**0.9441**	**0.9866**	**0.9649**

overhead means the sizes of inserted and padded packets divided by the total size of packets.

Evaluation Metrics. We measure the accuracy by using precision, recall, and F1-score as primary metrics. Moreover, we mainly pay attention to the recall value of malicious samples, which is a critical indicator of robustness. This is because the distribution of malicious samples exhibits significant drifts in the presence of evasion attacks, and thus causes noticeable decreases in the recall value of detectors.

5.2 Accuracy Evaluation

We conduct experiments on two datasets without evasion attacks, which allows us to confirm the correctness of the established baselines. According to Table 2, on the real-world dataset, Wedjat outperforms other unsupervised detection methods that claimed to achieve robust detection for some specific evasion attacks [19, 21] by achieving a 98.11% F1-score. Such performance is comparable to FS-Net deep learning-based detection which incurs high overheads. Moreover, Wedjat significantly improves the accuracy in terms of precision and recall over existing methods, where Wedjat achieves 93.87% precision and 98.66% recall. Similarly, on the public dataset, Wedjat achieves an accuracy of 96.71% F1 which is comparable to existing systens that are not robust against evasion attacks (cf. Section 5.3). Note that, Wedjat achieves similar accuracy on the enterprise dataset and the public dataset, which indicates Wedjat has stable performance across various network environments. Additionally, Wedjat only raises an average of 5.53 false alarms per hour, which can be manually managed by operators, according to a recent false positive alarm study [18].

Furthermore, we measure the accuracy under critical settings to clarify known issues [5, 25] in existing detection sytems [19, 21, 38]:

- **Datasets Bias.** We also use other public datasets [16, 17]. Specifically, Wedjat achieves 0.9097 and 0.9367 F1-score when detecting IoT attack traffic [17] and DNS-over-HTTP attack traffic [16], respectively. These results are similar to the results on the CIC datasets. The reason for mainly using the CIC public dataset is its significantly larger size than other public datasets.
- **Ablation Studies.** We disabled the packet embedding by directly using packet lengths, which resulted in 5.18% F1 drop. Meanwhile, we replace the causal network with traditional unsupervised ML used by Kitsune [38], which incurs 10.29% F1 drop.
- **Concept Drifting.** We trained the model on traffic data from Tuesday on the CIC dataset and tested it on data from the subsequent three days. We observed that Wedjat achieved an F1-score of 0.8022, which is significantly higher than the 0.5549 F1-score achieved by Whisper.
- **Domain Generalization.** We train the model on the public dataset and evaluate its accuracy on the dataset generated under real-world deployment. Wedjat achieves 0.7422 F1, outperforming the 0.6767 F1 achieved by FS-Net. All baseline models fail to detect attacks that differ from those in the training datasets.

5.3 Robustness Evaluation

To extensively validate the robustness against various evasion attacks, we implement five sophisticated evasion strategies that manipulate packets of all malicious traffic in testing sets. Moreover, we adjusted the parameters of these evasion strategies to set the data overheads and time overheads for each evasion strategy at 50%. Table 3 and Table 4 present the deterioration in detecting accuracy of our method and baselines across two datasets under different evasion strategies.

Robustness evaluation in real-world scenarios. We evaluate and compare Wedjat with the baselines on the real-world enterprise traffic. As shown in Table 3, we observe a significant decrease in recall and F1 of baseline methods. Specifically, Kitsune suffers from 49% ∼ 73% decrease in recall, where the random padding evasion strategy decreases recall and F1 to 49.33% and 63.23%. This indicates that 50% the malicious flows are misclassified as benign flows, and the attacker can effectively evade Kitsune. The detection performance of other baselines also exhibits significant decreases. For example, the recall of Hypervision drops to below 0.4 in the presence of WTF-PAD and DFD evasion strategies. Since such evasion strategies can obfuscate the statistical features that Hypervision relies on. Moreover, even if Hypervision analyzes inter-flow correlations, existing evasion attacks can still simultaneously obfuscate many flows. In comparison, our method achieves robust detection with a recall of over 89% across five evasion strategies.

Robustness evaluation on public datasets. To eliminate the effect of dataset bias, we further conduct robustness evaluation on public datasets. As shown in Table 4, Wedjat achieves over 90% precision, recall, and F1 scores on the public dataset, in the presence of three evasion strategies, random delaying, random padding, and WTF-PAD. Additionally, the decrease of recall for our model is bounded by 10%, thereby significantly outperforming other methods. Under the FRONT and DFD advanced evasion attacks, the recall of Wedjat is significantly higher than other malicious traffic detection methods.

Robustness evaluation with increasing overheads of evasion attacks. In addition, we compared the accuracy decreases under evasion attacks with various overheads. Figure 3 illustrates that, as the attacker invests more resources, the evading malicious traffic becomes more successful in evading detection by baselines. This is because larger overheads allow attackers to have more data or time resources to craft sophisticated evasion attacks, altering the original malicious features to a greater extent, and making them more difficult to detect. Figure 3 shows that, as evasion attacks introduce more overheads, the F1-score of our method remains above 80%,

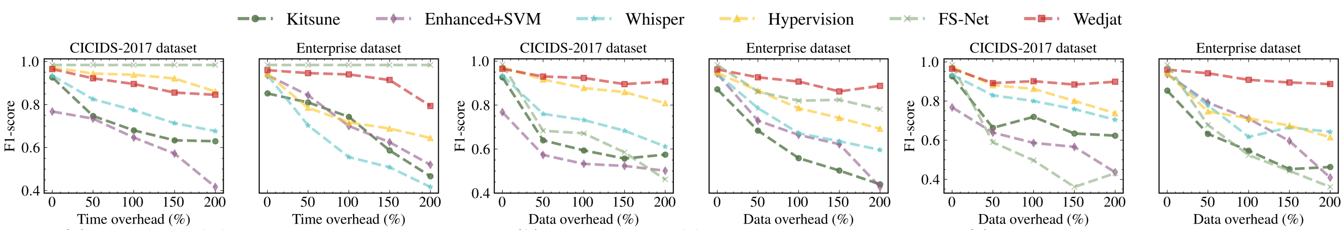
Table 3: Accuracy comparison under different evasion attacks with 50% overhead. (Enterprise Dataset)

Method	Random Delaying			Random Padding			FRONT			WTF-PAD			DFD		
	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1
Kitsune	0.9158	0.7270▼	0.8106▼	0.8806	0.4933▼	0.6323▼	0.8812	0.4944▼	0.6335▼	0.8754	0.4699▼	0.6115▼	0.8919	0.5849▼	0.7065▼
Enhanced+SVM	0.8663	0.8215▼	0.8433▼	0.8224	0.5870▼	0.6851▼	0.8541	0.7366▼	0.7910▼	0.8517	0.7258▼	0.7838▼	0.8524	0.7551▼	0.8008▼
FS-Net	-[1]	-	-	0.9775	0.7358▼	0.8396▼	0.9686	0.5215▼	0.6780▼	0.9718	0.5823▼	0.7283▼	0.9728	0.6289▼	0.7639▼
Whisper	0.8978	0.5816▼	0.7059▼	0.9066	0.6424▼	0.7519▼	0.9110	0.6779▼	0.7773▼	0.9078	0.6517▼	0.7587▼	0.8872	0.5407▼	0.6719▼
Hypervision	0.8913	0.7152▼	0.7936	0.8894	0.7012▼	0.7842	0.8813	0.6474▼	0.7465	0.8200	0.3973▼	0.5353▼	0.7964	0.3541▼	0.4902▼
Wedjat	**0.9372**	**0.9517**	**0.9444**	**0.9337**	**0.8986**	**0.9158**	**0.9366**	**0.9424**	**0.9395**	**0.9351**	**0.9190**	**0.9269**	**0.9360**	**0.9331**	**0.9345**

[1] FS-Net is only based on packet length and is immune to the Random Delaying Evasion Strategy.
[2] We mark ▼ for a significant performance degradation compared to the non-evasion scenario.

Table 4: Accuracy comparison under different evasion attacks with 50% overhead. (CICIDS-2017 Dataset)

Method	Random Delaying			Random Padding			FRONT			WTF-PAD			DFD		
	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1
Kitsune	0.9326	0.6233▼	0.7472▼	0.9161	0.4916▼	0.6399▼	0.9201	0.5183▼	0.6631▼	0.9151	0.4850▼	0.6339▼	0.8897	0.3633▼	0.5159▼
Enhanced+SVM	0.6981	0.7750	0.7345	0.6156	0.5366▼	0.5734▼	0.6516	0.6266▼	0.6389▼	0.6616	0.6550▼	0.6582▼	0.6178	0.5416▼	0.5772▼
FS-Net	-	-	-	0.9391	0.4883▼	0.6425▼	0.9694	0.4233▼	0.5893▼	0.9652	0.3700▼	0.5349▼	0.9799	0.6516▼	0.7827▼
Whisper	0.8996	0.7616▼	0.8249	0.8874	0.6700▼	0.7635▼	0.9003	0.7683▼	0.8291	0.8671	0.5550▼	0.6768▼	0.8583	0.5150▼	0.6437▼
Hypervision	0.9603	0.9283	0.9441	0.9581	0.8783	0.9165	0.9551	0.8166▼	0.8805	0.9514	0.7516▼	0.8398	0.9494	0.7200▼	0.8189
Wedjat	0.9394	**0.9050**	**0.9219**	0.9403	**0.9200**	**0.9301**	0.9358	**0.8516**	**0.8917**	0.9394	**0.9050**	**0.9219**	0.9340	**0.8266**	**0.8771**



(a) Random delaying strategy. **(b) Random padding strategy.** **(c) FRONT injection strategy.**

Figure 3: Comparison of F1-scores with baselines under various evasion attacks with increasing overheads.

which indicates a slight drop in performance under highly potent evasion attacks. Overall, attackers can increase the number of injected bytes or delayed time intervals, which incur more overheads, to more effectively evade existing methods, whereas they cannot evade robust detection of Wedjat.

5.4 Efficiency Evaluation

We analyze the default setting of the causal network in Figure 4. We observe that the average prediction latency for a packet is 0.1213 seconds. Meanwhile, our model can produce detection results for each packet within 0.125 seconds. Additionally, we analyze the effect of different network scales on detection latency. Figure 5 indicates that, when the number of nodes is less than 50, the average detection latency is bounded by 0.5 seconds. However, as the scale of the network increases to 3×25 and 4×25, the average detection latency exhibits gradual increases and exceeds 1.000s. Such observation underscores the impact of network scale on packet inference efficiency, offering valuable insights for further optimizing network structures. In addition, We measure the overheads of the packet embedding module and the casual network module, which incur latency of 0.0034s and 0.1180s, respectively. Note that, Wedjat incurs lower detection latency which is 6.56 times lower than that of the existing method, i.e., FS-Net, which incurs 0.7965s per flow latency.

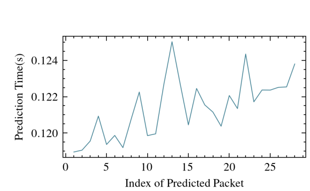


Figure 4: Prediction latency for each packet (3 flows × 10 packets in each bag).

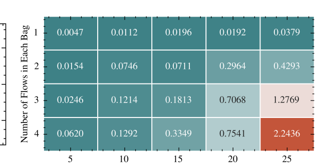


Figure 5: Average packet prediction latency for different scales of casual networks.

6 Related Work

ML based Malicious Traffic Detection. ML based detection captures network attacks by investigating the features of traffic, which outperform traditional signature-based methods [49, 57]. For supervised detection, Barradas *et al.* developed Flowlens that employed random forests to learn the distribution features on programmable switches [7]. Similarly, Zhou *et al.* developed NetBeacon that implemented decision trees on Intel Tofino switches [61]. Siracusano *et al.* developed N3IC that installed binary neural networks on SmartNICs [47]. Moreover, Holland *et al.* [23] developed nPrintML that learned every byte in packet headers. For unsupervised detection, Mirsky *et al.* developed Kitsune that learned packet-level features by using autoencoders [38]. Tang *et al.* [50] detected malicious HTTP traffic with unsupervised language models. Bilge *et al.* [9] clustered features extracted from NetFlow data to capture traffic of malware. Note that, these methods are not robust against evasion attacks [1, 13, 20, 22, 26, 36]. Additionally, existing methods extract traditional non-robust features, and employ causal detection to weight and select these features. Thus, the existing methods, such as the approach developed by Zeng *et al.* [58], are vulnerable to manipulations by evasion attacks

Encrypted Traffic Detection. Most existing methods cannot effectively capture encrypted attack traffic, as traffic encryption conceals packet payloads and thus invalidates signature-based detection [49, 57] and Deep Packet Inspection(DPI) [40, 43]. Meanwhile, encryption protocols obfuscate traffic features to evade ML-based detection. Most existing detection systems for encrypted traffic are task-specific [4, 12]. For example, Zheng *et al.* detected crossfire attack detection on SDN switches [60]. Similarly, Xing *et al.* designed a programmable switch based method to capture link flooding attacks [56]. Tegeler *et al.* developed BotFinder that analyzes time-scale flow features to detect encrypted traffic of malware communications [51]. Anderson *et al.* detected malware encrypted traffic via TLS headers [3]. Moreover, graph learning methods are leveraged to capture various encrypted traffic [21, 24, 39]. Note that, the methods focus on classifying traffic of known Categories, which is entirely different to our malicious traffic detection for recognizing unknown attacks.

Encrypted Traffic Classification. Wedjat identifies encrypted traffic associated with malicious behaviors, which is different from studies on encrypted traffic classification, which infer if encrypted traffic is generated by certain applications [45] to jeopardize user privacy. For instance, web fingerprint attacks classify encrypted Tor traffic to infer the websites accessed by users [42]. Similarly, Siby *et al.* classified encrypted DNS traffic [46]. Moreover, Bahramali *et al.* classified the encrypted traffic generated by instant messaging applications, which can infer the content of the messages [6]. Ede *et al.* classified the encrypted traffic generated by Android apps [53].

Causal Analysis. Causal analysis discerns and quantifies causal relationships (Causality) between variables, e.g., Causal Graphical Models (CGMs)[35], Structural Causal Models (SCMs)[11], and other probabilistic networks. CGMs, particularly Bayesian Networks, represent causal assumptions and dependencies via directed acyclic graphs (DAGs). SCMs extend CGMs by incorporating specific functional relationships and counterfactual reasoning. Other frameworks like Markov Random Fields (MRFs) and Conditional Random Fields (CRFs) explore dependencies using undirected graphs. Causal analysis is widely used in domain generalization[62],such as Unaligned Image-to-Image Translation[55], Motion Prediction[33], and Recommendation Systems[29]. In this paper, we design the Causal Network to model the complex relationships among packets, which is different from these previous works, i.e., we bag the variables (packets) to effectively analyze inter-flow relationships, and compress the network for efficient detection.

7 Conclusion

In this paper, we develop Wedjat, which utilizes a causal network to model benign interactions from packets among relevant flows, such that it recognizes abnormal causality that represents malicious traffic and disrupted causality incurred by evasion attacks. We extensively evaluate Wedjat with millions of flows collected from a real enterprise. The experimental results demonstrate that Wedjat achieves an accuracy of 0.957 F1-score when detecting various advanced attacks. Notably, five sophisticated evasion attacks, which have successfully evaded all existing methods, are accurately detected by Wedjat with over 0.915 F1. This demonstrates Wedjat exhibits exceptional capability in robustness against evasion. Meanwhile, Wedjat maintains an outstanding detection latency, predicting each packet in less than 0.125 seconds.

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A Algorithm

A.1 Distance-Based K-Means Algorithm

The algorithm 1 is a greedy search for distance-based clustering[14] in the packet embedding module.

Algorithm 1: Distance-based K-Means

Input : Packets Dataset $D_{S_{\boldsymbol{p}}} = \{(\boldsymbol{p}^i, y^i)\}_{i \geq 1}^{n_{S_{\boldsymbol{p}}}}$, Number of clusters N_c, distance function $d(\cdot, \cdot)$

Output: Cluster assignments $\mathscr{C}^* = \{C_1, ..., C_{N_c}\}$

Initialize N_c clusters $C_1, C_2, \ldots, C_{N_c}$ randomly where each cluster C_j is a set containing n_j points and each point is a member of exactly one cluster;

repeat

  for $\boldsymbol{p}^i$ *in* $D_{S_{\boldsymbol{p}}}$ **do**

    compute $j^* = \arg\max_j \frac{1}{|C_j|} \sum_{\boldsymbol{p}' \in C_j} d(\boldsymbol{p}^i, \boldsymbol{p}')$;

    Assign each packet vector point $\boldsymbol{p}^i$ to the nearest cluster center C_{j^*} based on the max average similarities;

  end

  Update clusters. $C_j = \{\boldsymbol{p}^i | j^* = j\}$;

until *convergence*;

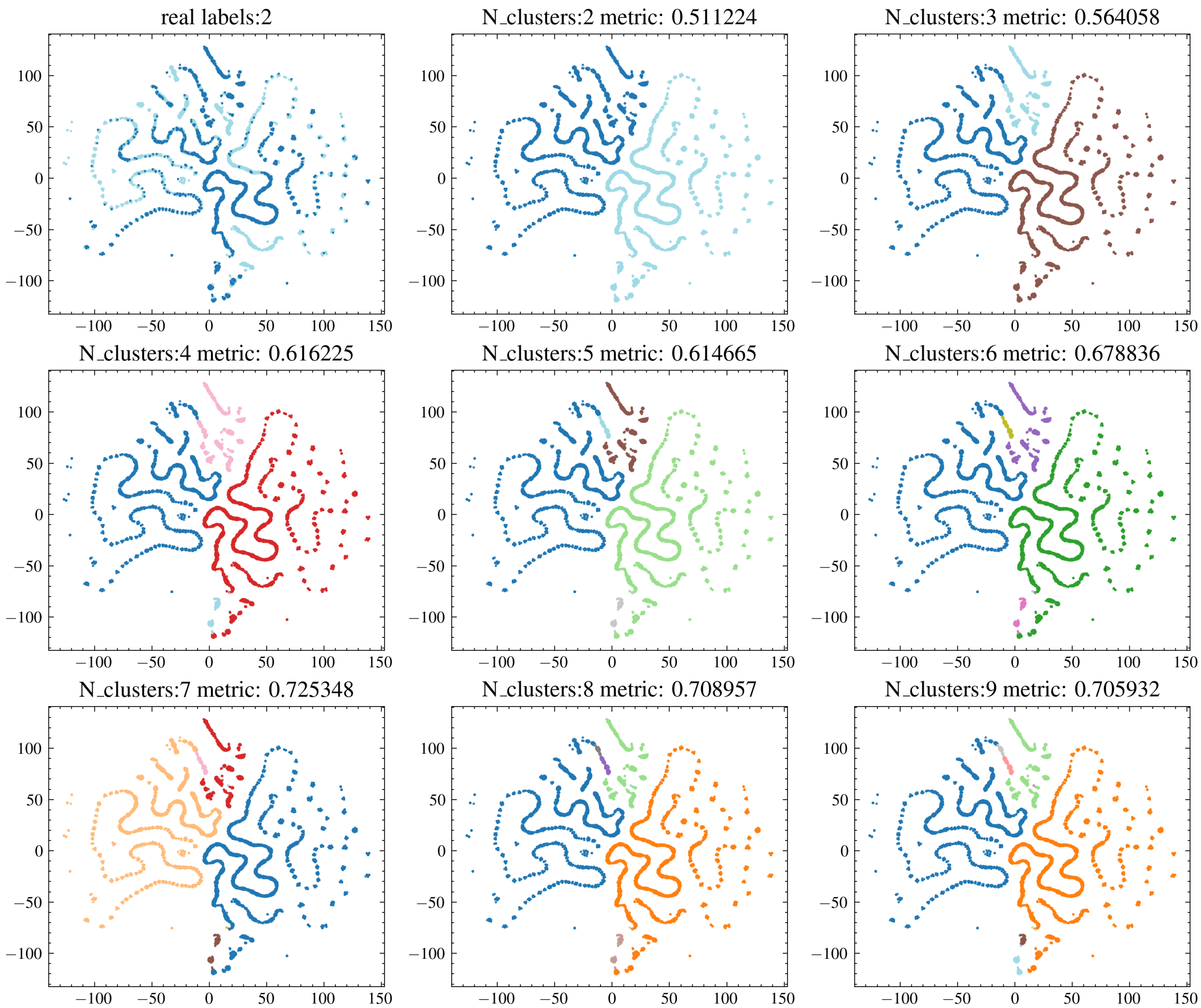


Figure 6: Clustering Results under different number of clusters. For packet-level multi-dimensional features clustering, we employed the T-SNE algorithm to display the clustering results for different values of parameter N_c. The metric refers to the output value of the objective function in equation (6).

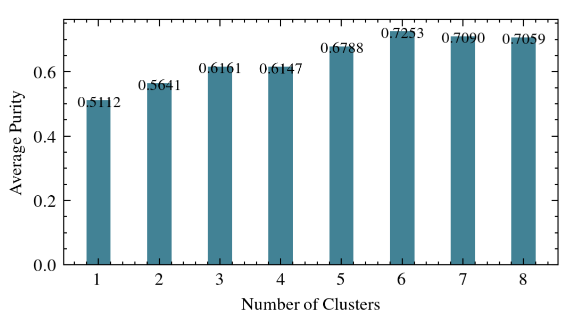


Figure 7: Clustering Results of different numbers of clusters.

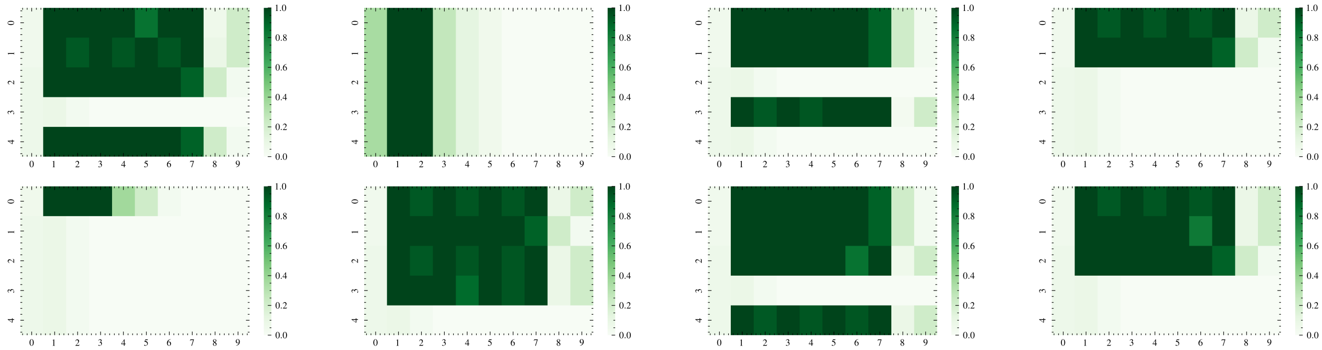
A.2 Foundational Network Construction

Algorithm 2 demonstrates the construction of the foundational network, which models the interactions regulated by behaviors and Internet protocols. It is divided into two steps. Firstly, to model the within-flow packet interactions, we assign edges for successive packets, which represent the continuous behaviors. Secondly, to model the between-flow interactions governed by protocols, edges are established for packets at the same location of different flows.

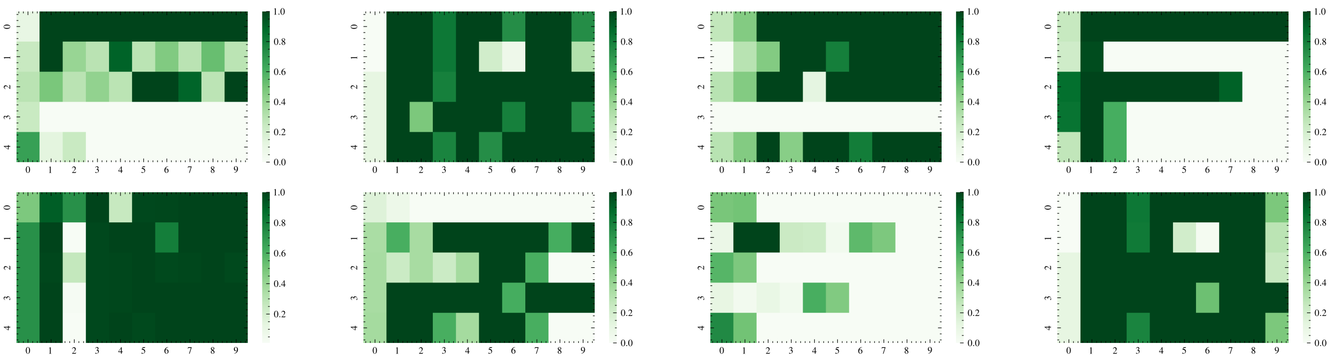
B Parameter Selection of Packet Embedding

The first training phase of our method is to obtain the optimal clustering results of the packet embedding module. It simultaneously clusters malicious and benign packets from the training set, aiming to purify each cluster as much as possible, such that the ratio of malicious or benign packets in each cluster approaches 1. This process involves optimizing N_c, namely the number of clusters. We select the parameter and clustering results that maximize cluster purity as the output model for the first training phase.

The parameter N_c is optimized by maximizing the average purity of all clusters, as determined by the formula 6. As Figure 6 shows,



(a) Patterns of Benign Traffic Bags.



(b) Patterns of Malicious Traffic Bags.

Figure 8: Different patterns of benign and malicious traffic. Each bag originates from the same IP Pair. Each row signifies a flow, with each cell representing a packet's length. Darker shades indicate larger values.

Algorithm 2: Foundational Network Construction

Input : Number of flows in each bag N, Number of packets in each flow M

Output : Edges Set $Edges = \{e\}$

Denote $e := Node_i \Rightarrow Node_j$.

for $i = 1, 2, \ldots, N$ **do**

  for $j = 1, 2, \ldots, M$ **do**

    $Edges \cup \left\{Node_{i-1,j} \Rightarrow Node_{i,j}\right\}$, if $i \neq 1$;

    $Edges \cup \left\{Node_{i-1,j} \Rightarrow Node_{i,j}\right\}$, if $j \neq 1$;

  end

end

we visualize the process of selecting this parameter, presenting the clustering results and average purity for different numbers of clusters. Figure 7 below indicates that when N_c equals 7, the average purity of all clusters reaches its maximum value of 0.725348. Therefore, we fix N_c at 7 and utilize the clustering results as the model in the first module. This model is employed in the packet classification during the detection phase.

C Empirical Observations

We randomly choose and visualize several malicious bags and benign bags respectively in Figure 8. We observed that there is a significant difference in the between-flow relationships between malicious and benign traffic. Specifically, the interactions in malicious bags appear more irregular and elusive, which demonstrates that the between-flow packet interactions are distinguishable and critical factors in malicious traffic detection.