Detecting Unknown Encrypted Malicious Traffic in Real Time via Flow Interaction Graph Analysis

Effective and Efficient Detection for Encrypted Malicious Traffic

Chuanpu Fu[1], Qi Li[1,2], Ke Xu[1,2]

[1]Tsinghua University, Beijing, China; [2]Zhongguancun Lab, China

1. Backgrounds: Traffic Encryption

- Traffic encryption is widely adopted on the Internet.

May 2019, 94% of all Google web traffic is encrypted.[1]

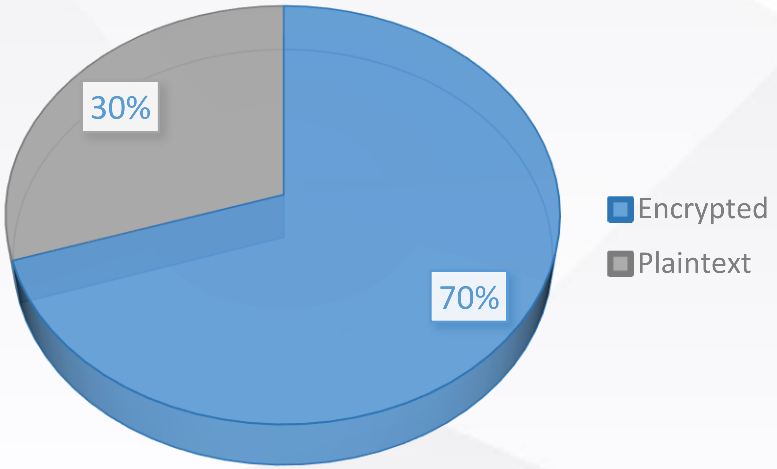
Nearly 80% of web pages loaded by Firefox use HTTPS.[2]

Over 98% Alexa top 1k websites support HTTPS.

[1] https://transparencyreport.google.com/https/overview?hl=en
[2] Predicts 2017: Network and Gateway Security.

1. Backgrounds: Abused Traffic Encryption

- Traffic Encryption is double-edged.
  - Attackers abuse traffic encryption to conceal their behaviors, e.g., data breach, and exfiltration.
  - It is reported that, 70% attacks were constructed by encrypted traffic in 2020.



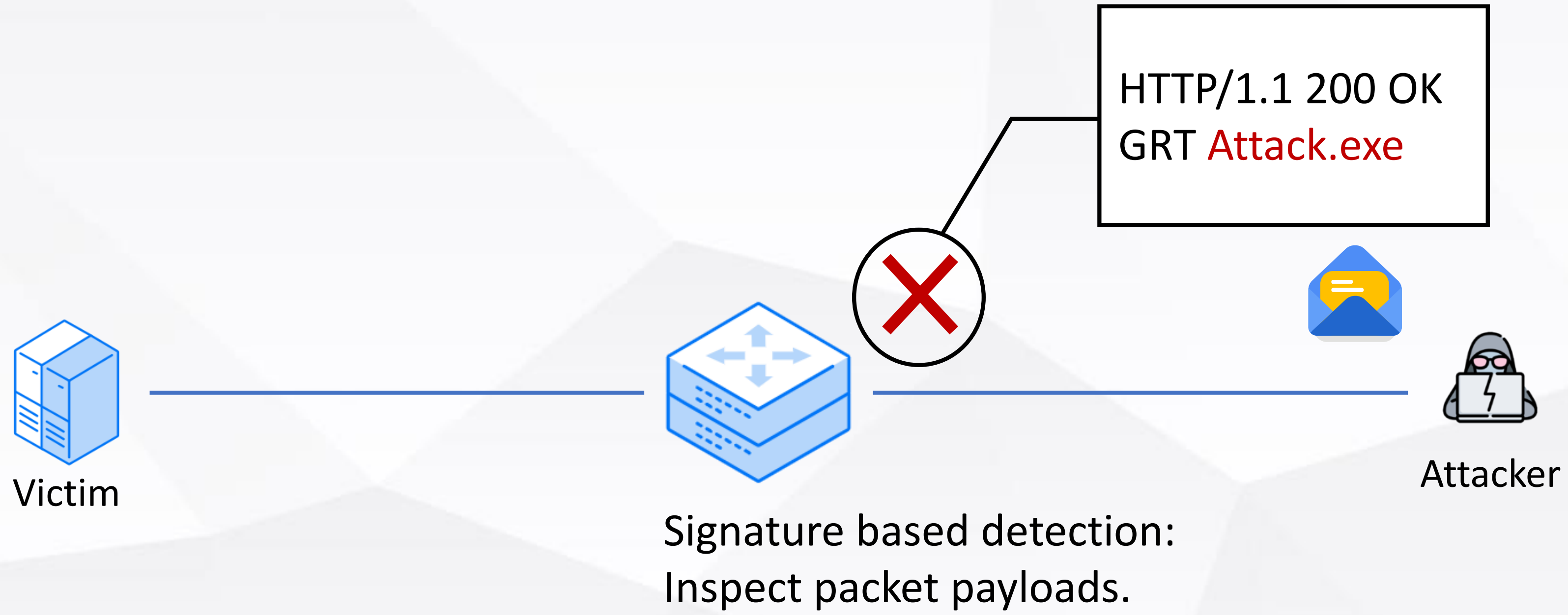
Over 70% attacks were constructed by encrypted attack traffic.

[3] Cisco Encrypted Traffic Analytics White Paper, Cisco.

1. Backgrounds: Malicious Traffic Detection

- Attackers can easily evade the existing detection via traffic encryption.

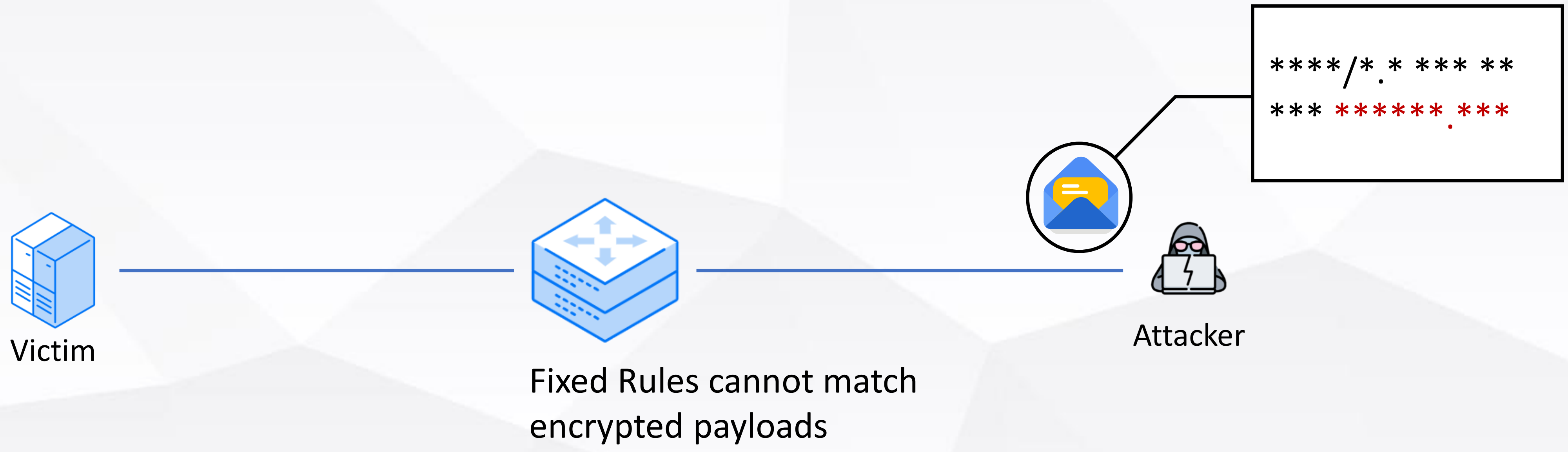
Traditional signature-based method:



1. Backgrounds: Malicious Traffic Detection

- Attackers can easily evade the existing detection via traffic encryption.

  Traditional signature-based method: Deep Packet Inspection (DPI) is invalid.



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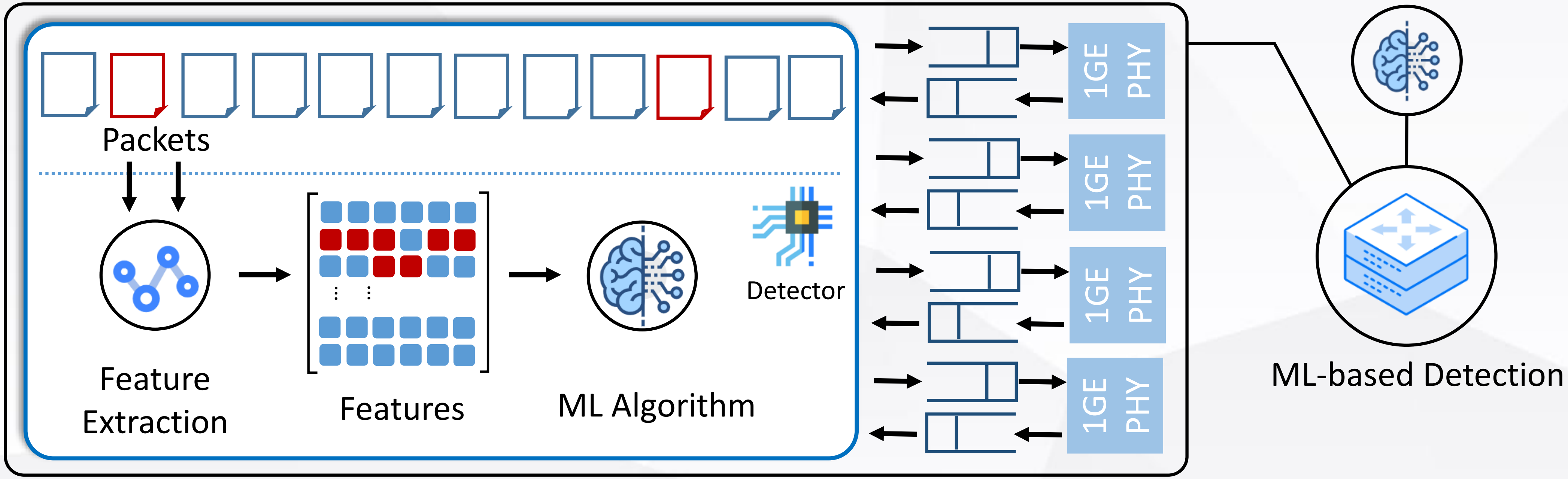
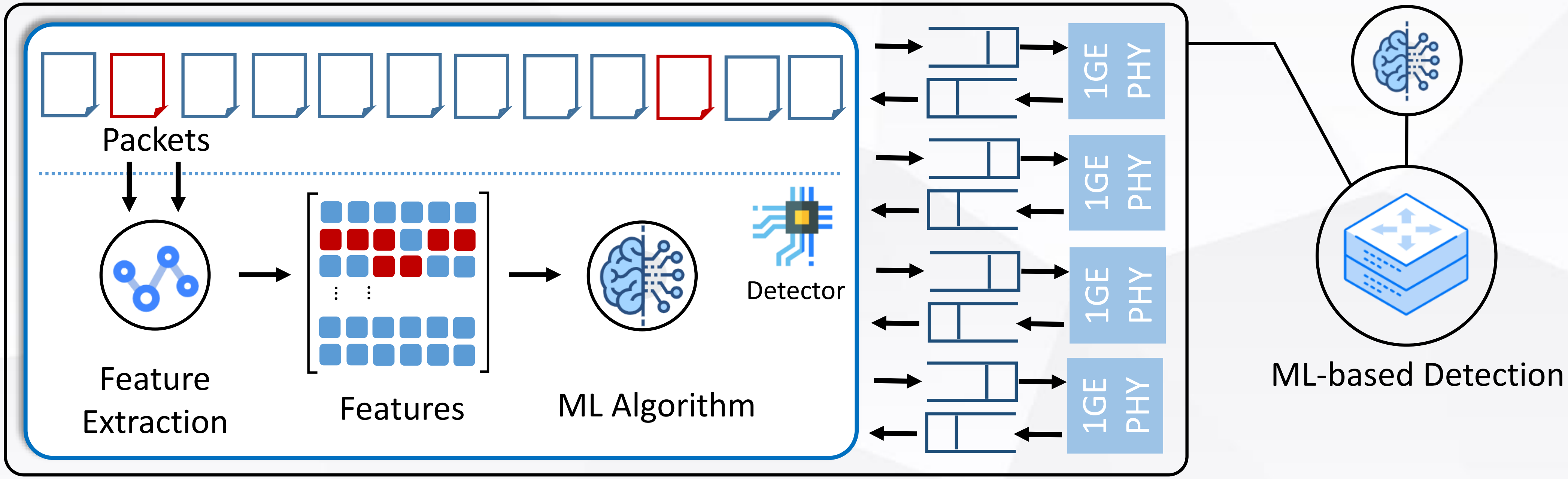


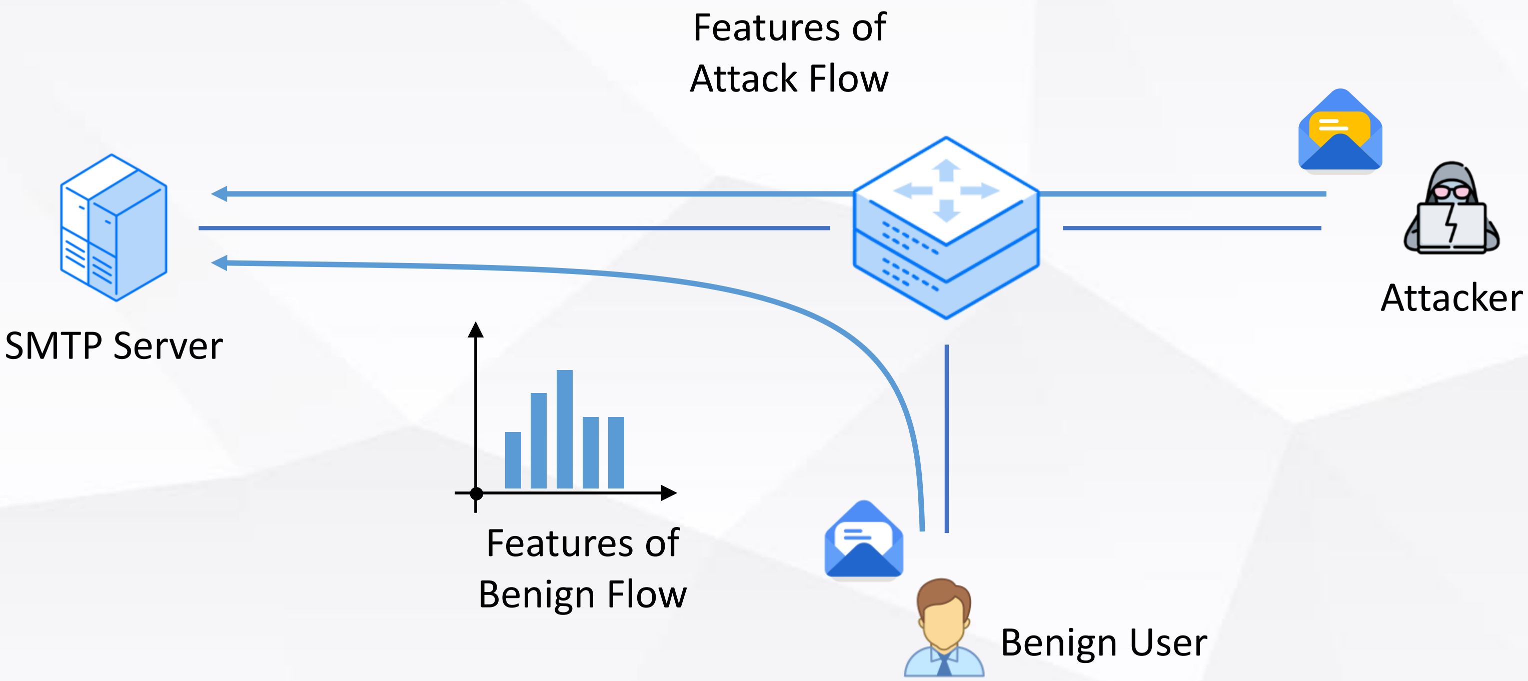
1. Backgrounds: Malicious Traffic Detection

- Attackers can easily evade the existing detection via traffic encryption.
- Advanced ML-based detection cannot detect such attack either.
  - *Encrypted malicious flows with benign traffic patterns.*



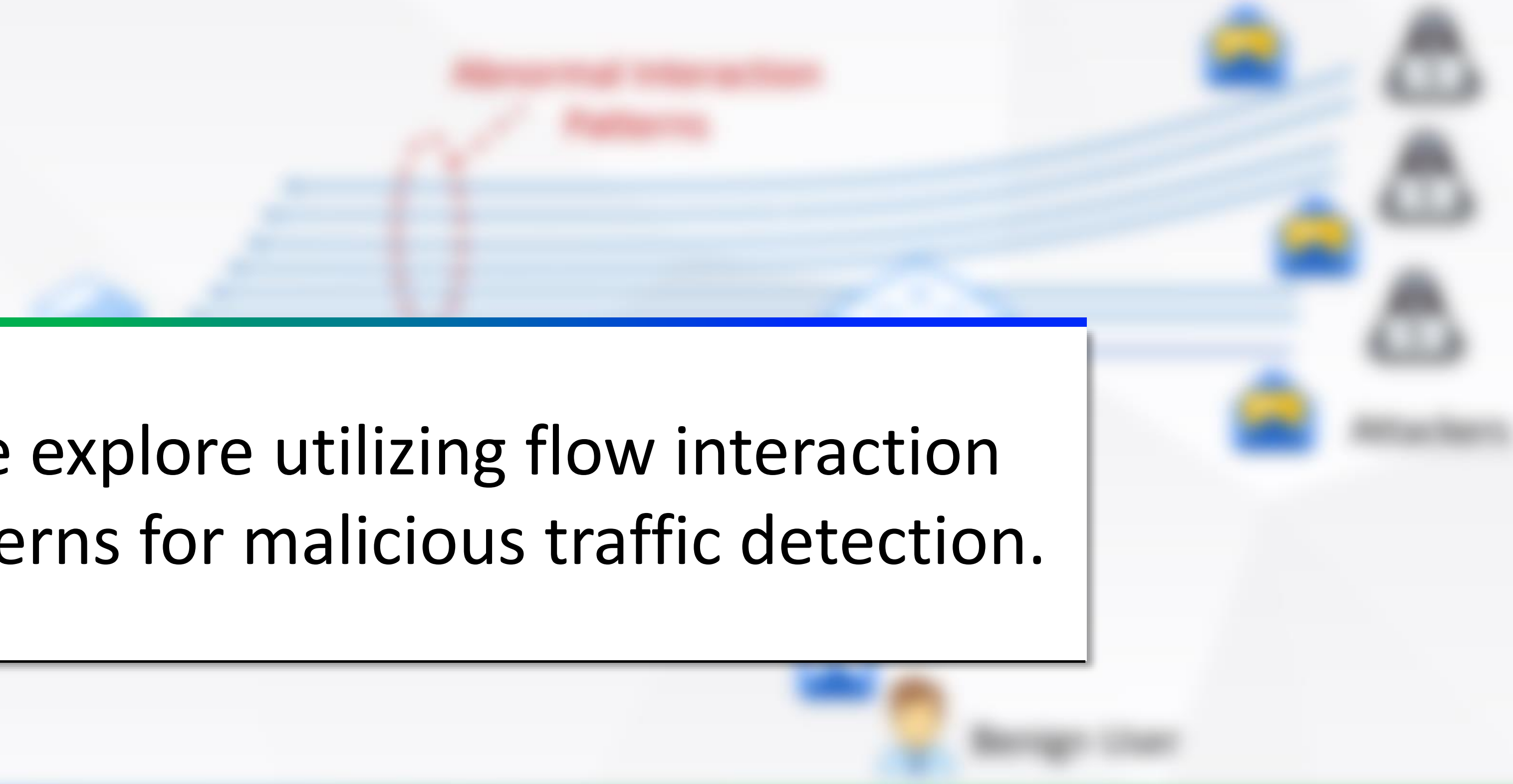
1. Backgrounds: Encrypted Attack Traffic Evades Detection

- Advanced ML-based detection cannot detect such attack either.
  - Benign SMTP-over-TLS Traffic & Encrypted Spam Traffic.
  - Traditional traffic features cannot differentiate encrypted malicious traffic.



2. Motivation: Interaction Patterns

- It is still possible to detect encrypted malicious traffic according to interaction patterns.
  - The interactions between spambots and SMTP servers are significantly frequent.



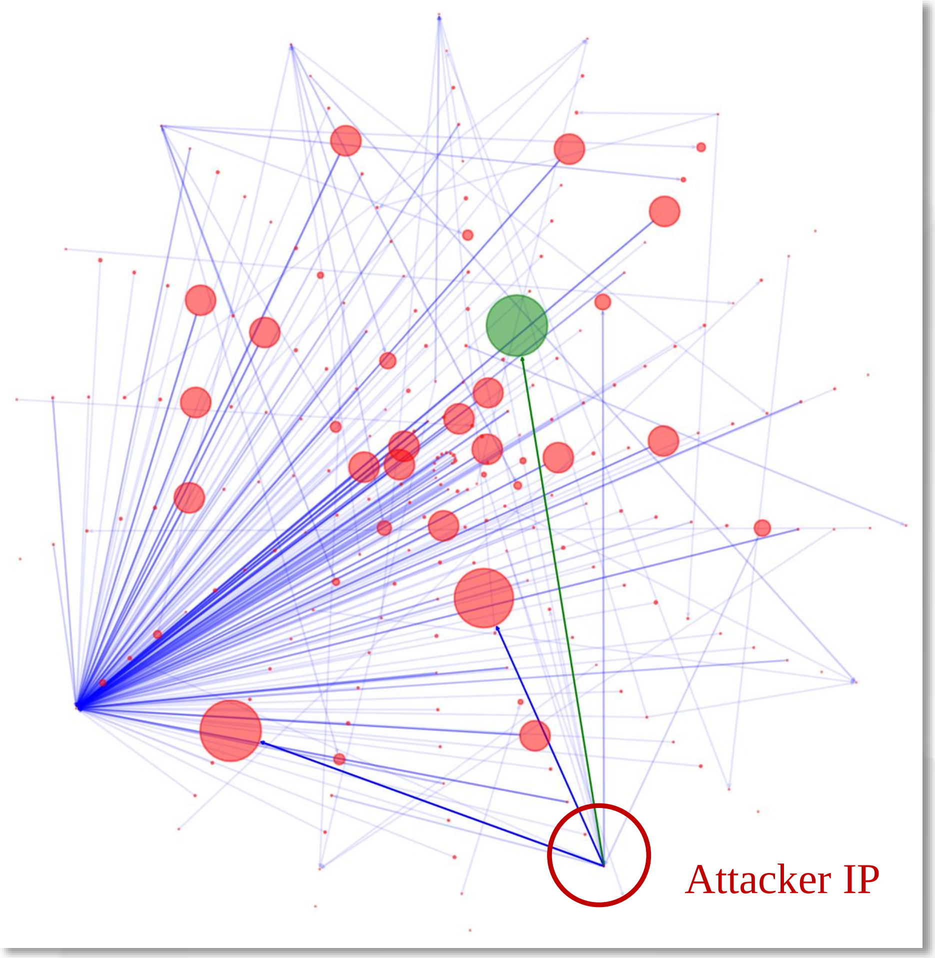
We explore utilizing flow interaction patterns for malicious traffic detection.

2. Motivation: Flow Interaction Graph

- We use a graph to represent the interaction patterns.
  - Vertices → IP addresses.
  - Edges → Flows

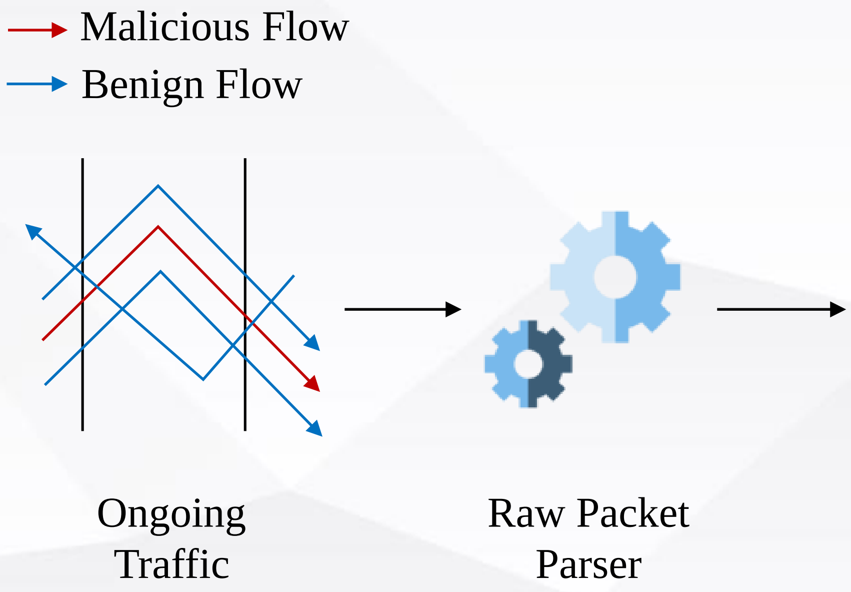
- We use unsupervised graph learning to detect the attacks, without requiring any prior knowledge.

Flow Interaction Graph



3. Design: Overview

➢ Module 1: Graph Construction Module.



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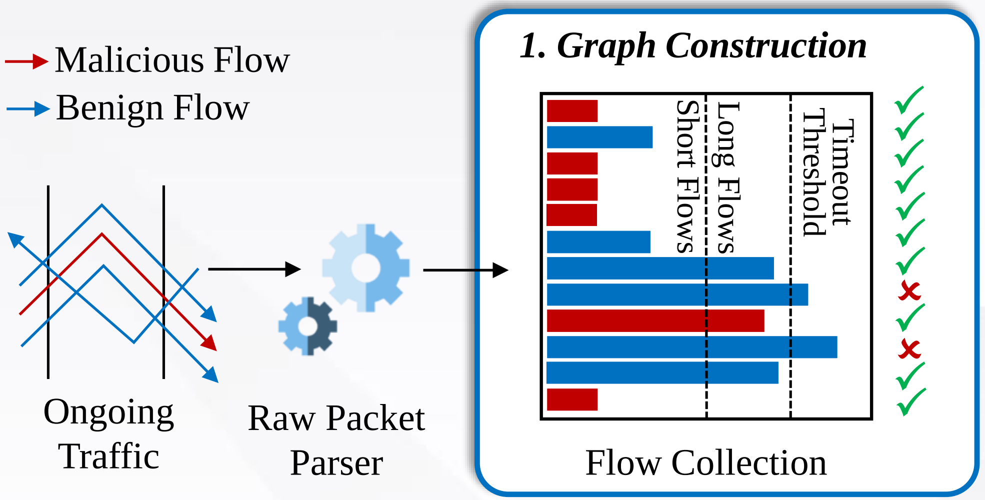

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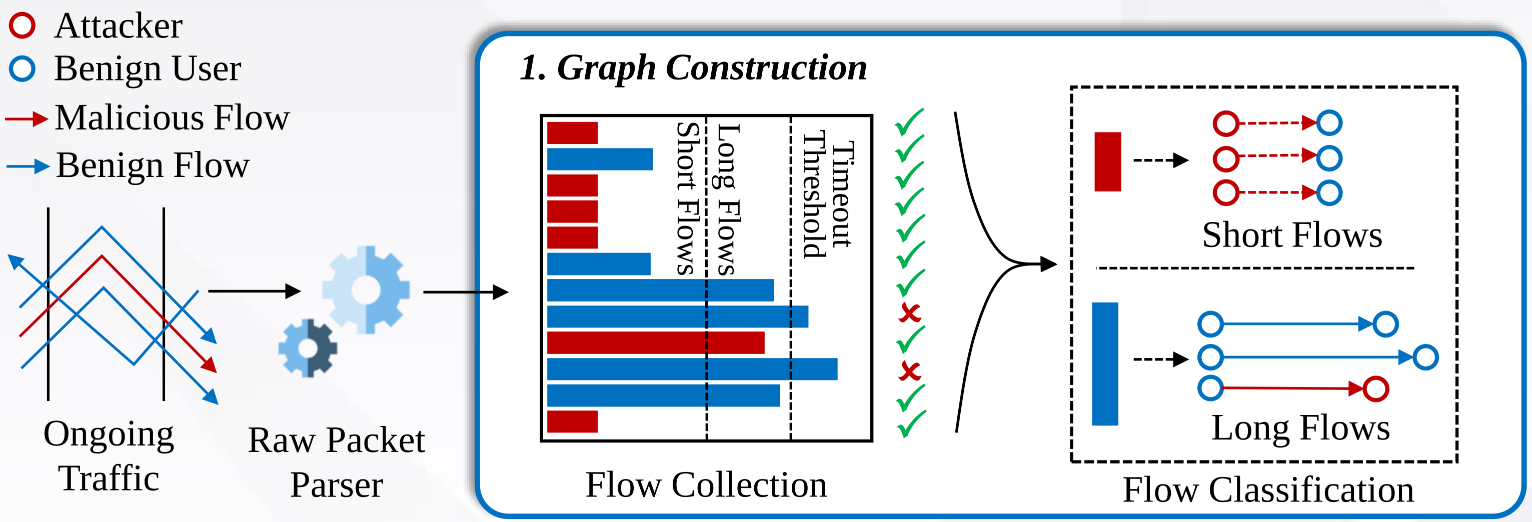

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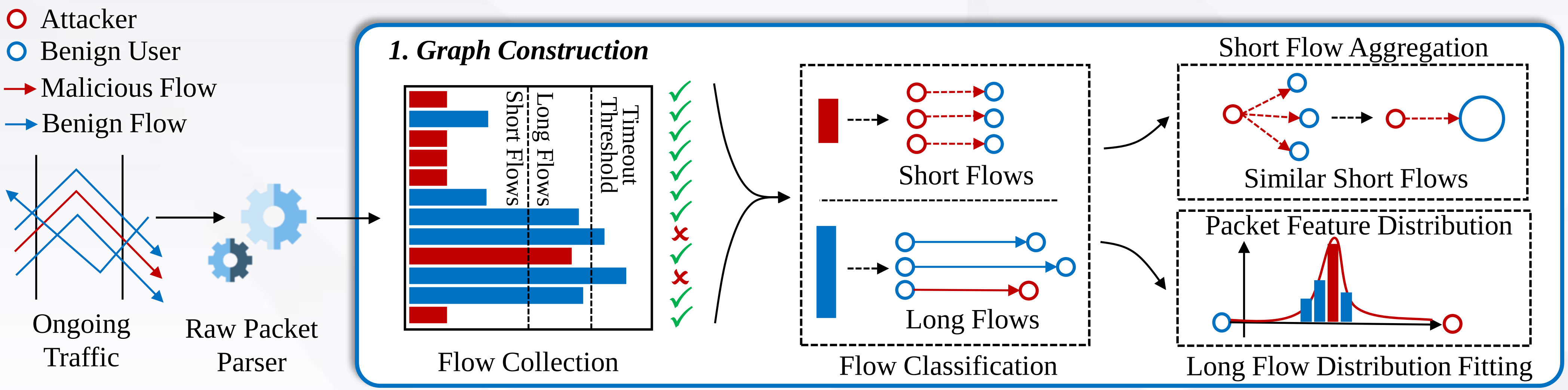

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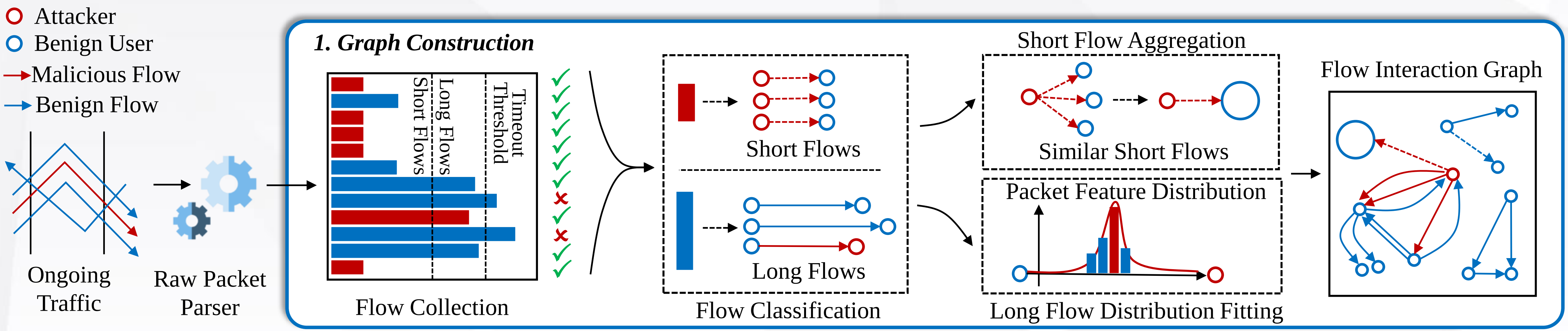

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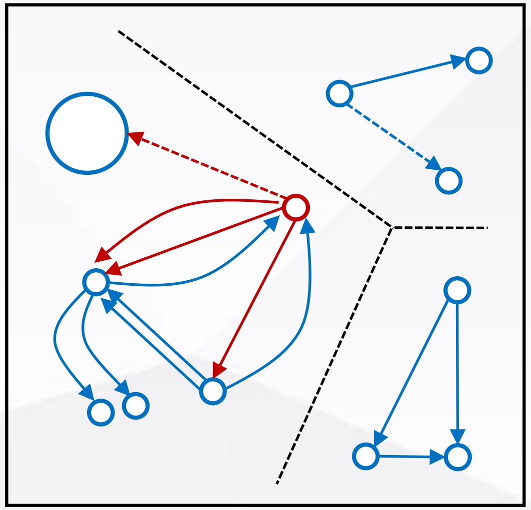
- Module 2: Graph Pre-Processing Module.

Flow Interaction Graph



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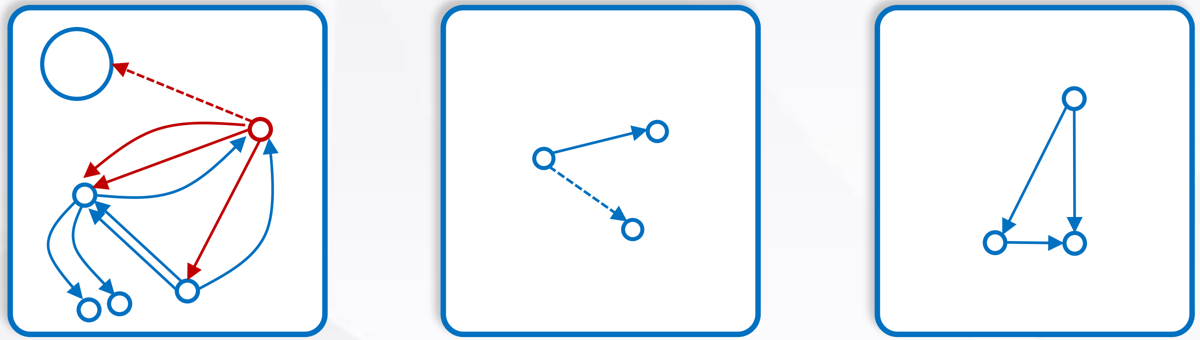
- Module 2: Graph Pre-Processing Module.

Strongly Connected Components



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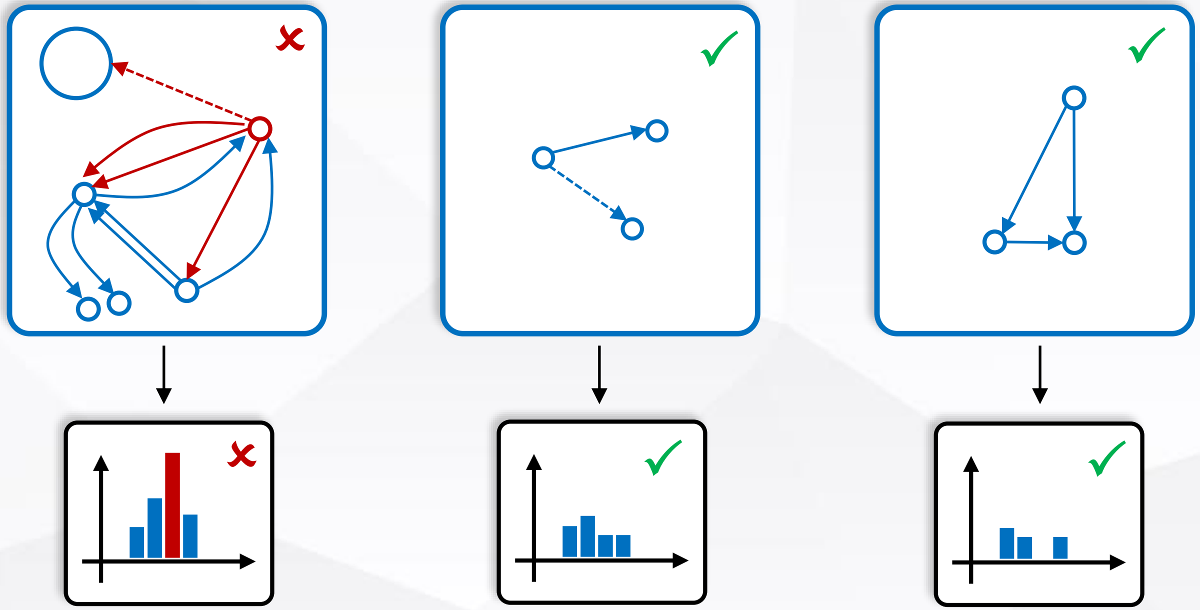
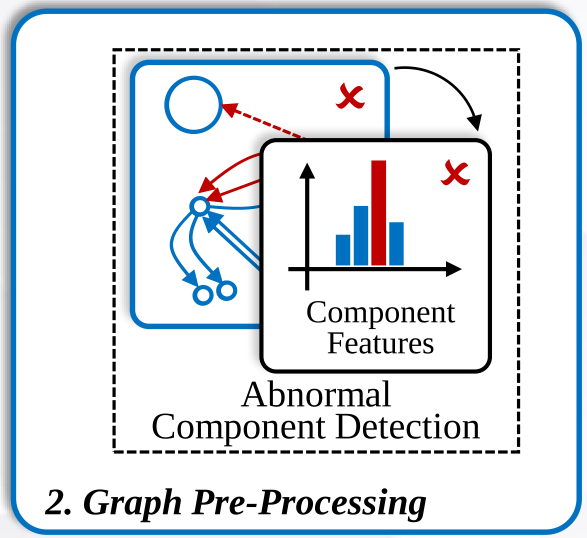


Component Statical Features

3. Design: Overview

- Module 2: Graph Pre-Processing Module.



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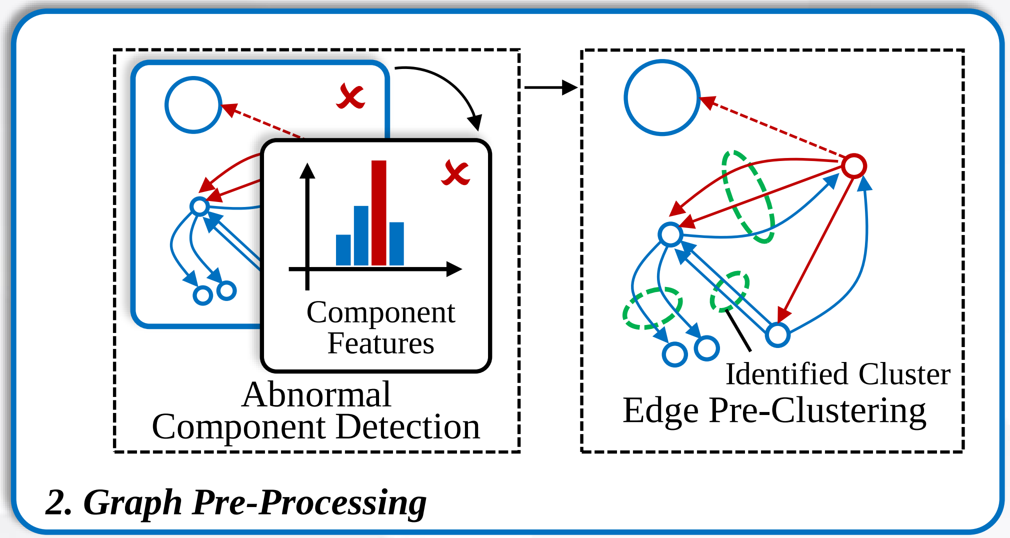

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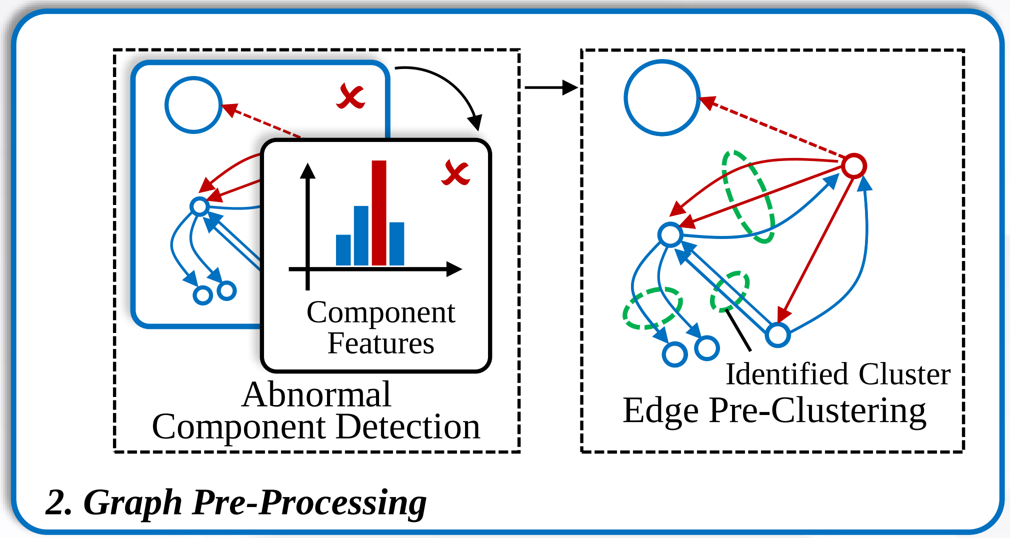
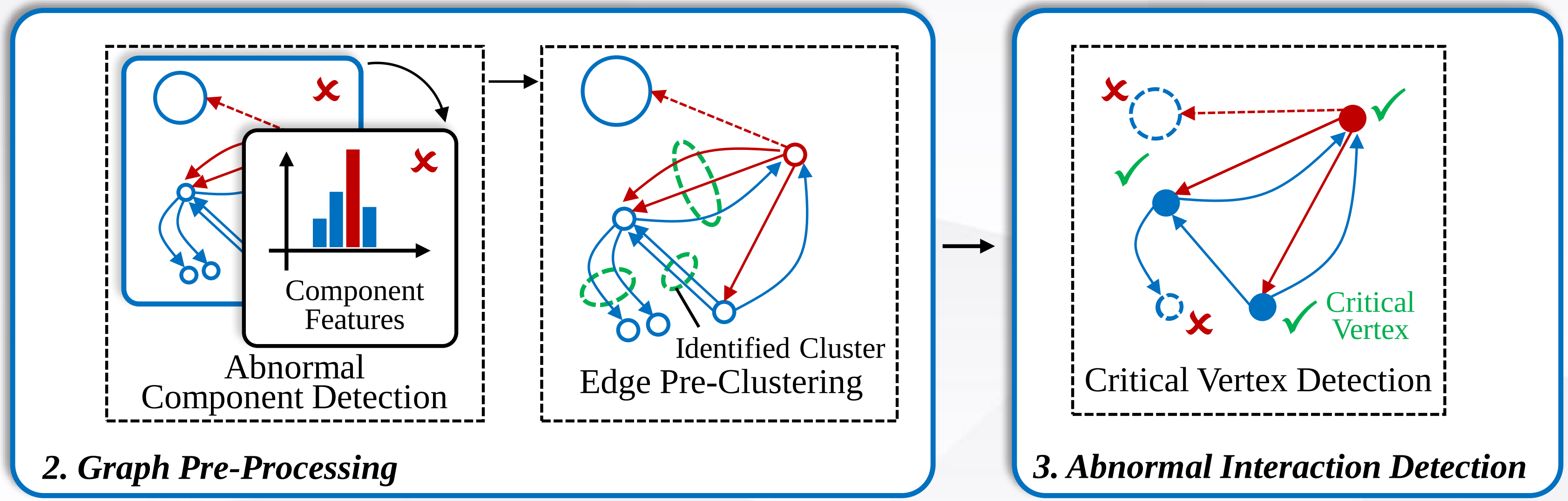


3. Design: Overview

- Module 3: Graph Detection Module.



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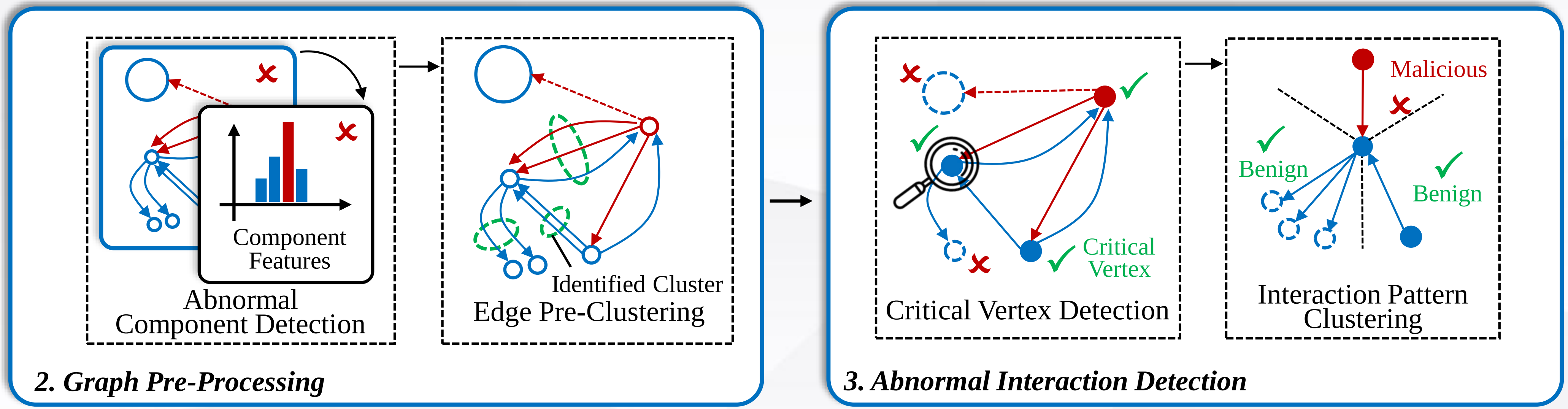

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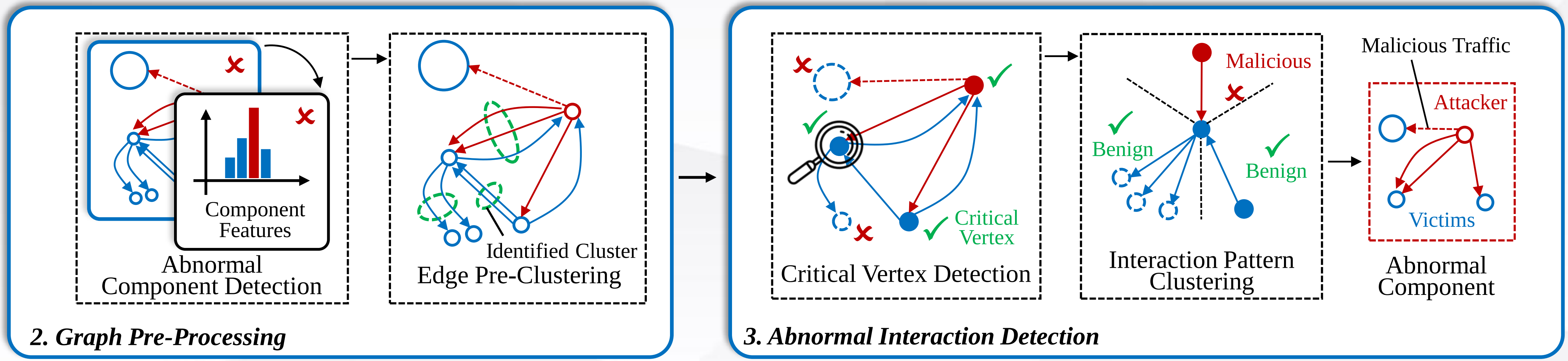

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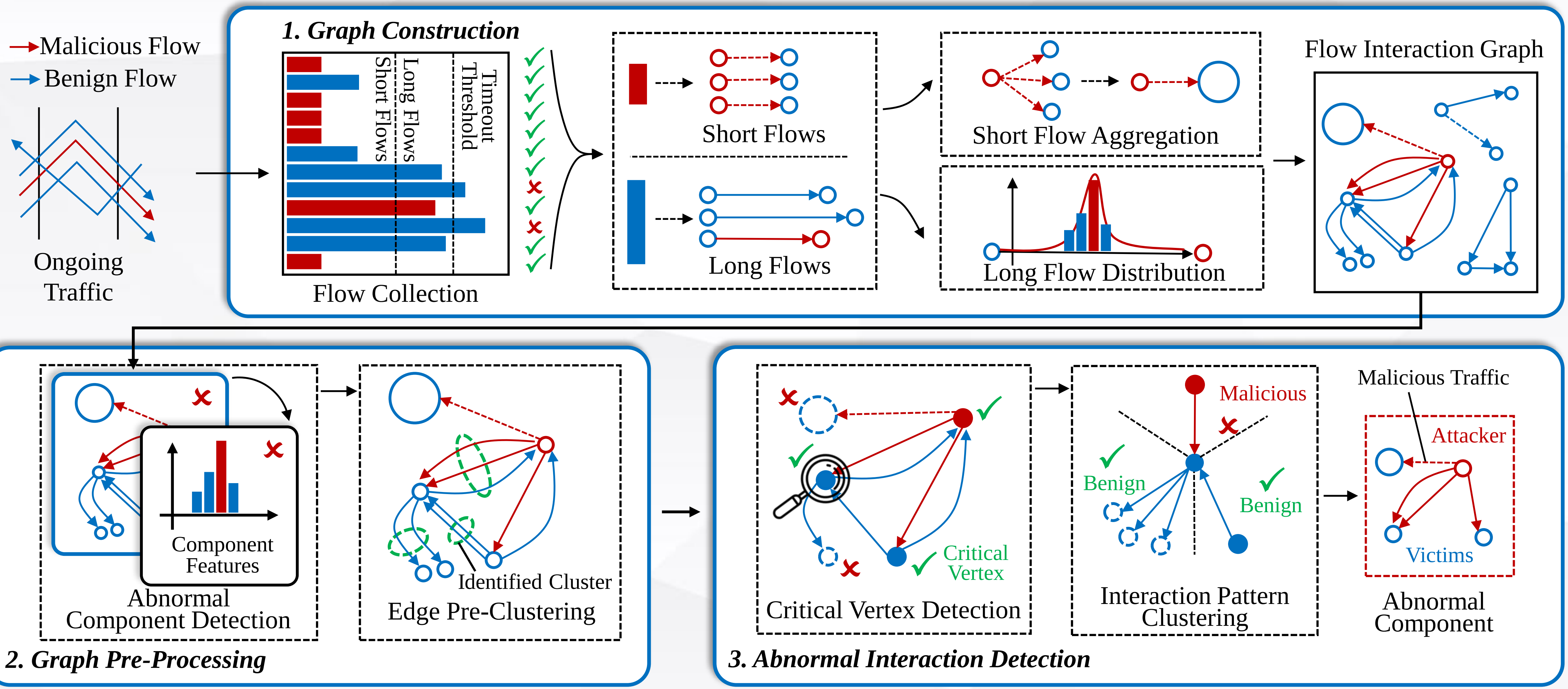


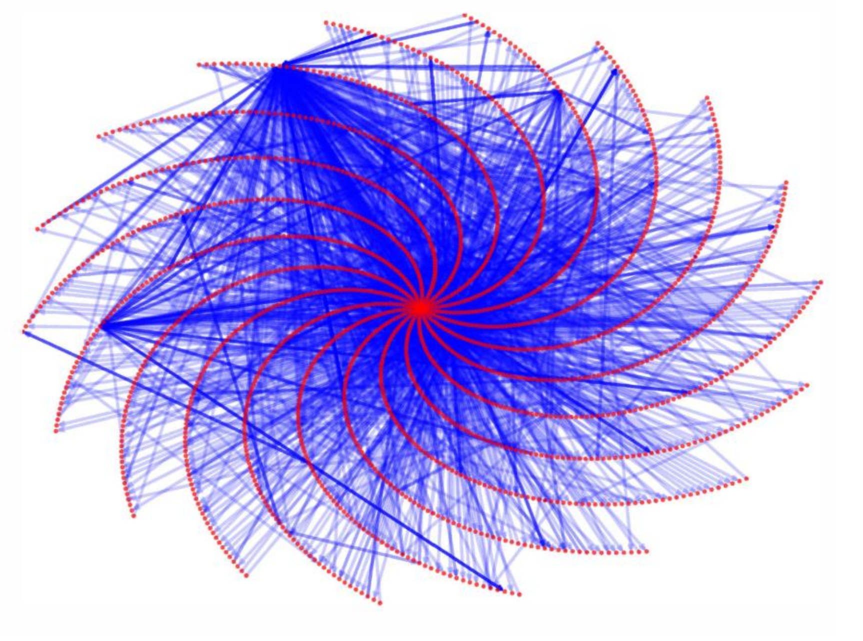
3. Design: How to reduce graph density?

- Complex flow interaction patterns.
  1. Over 50,000 active hosts reside in AS2500.
  2. Over 3M flows per hour.

- We cannot use one edge to denote one flow and use one vertex to denote one IP → *dependency explosion problem*.

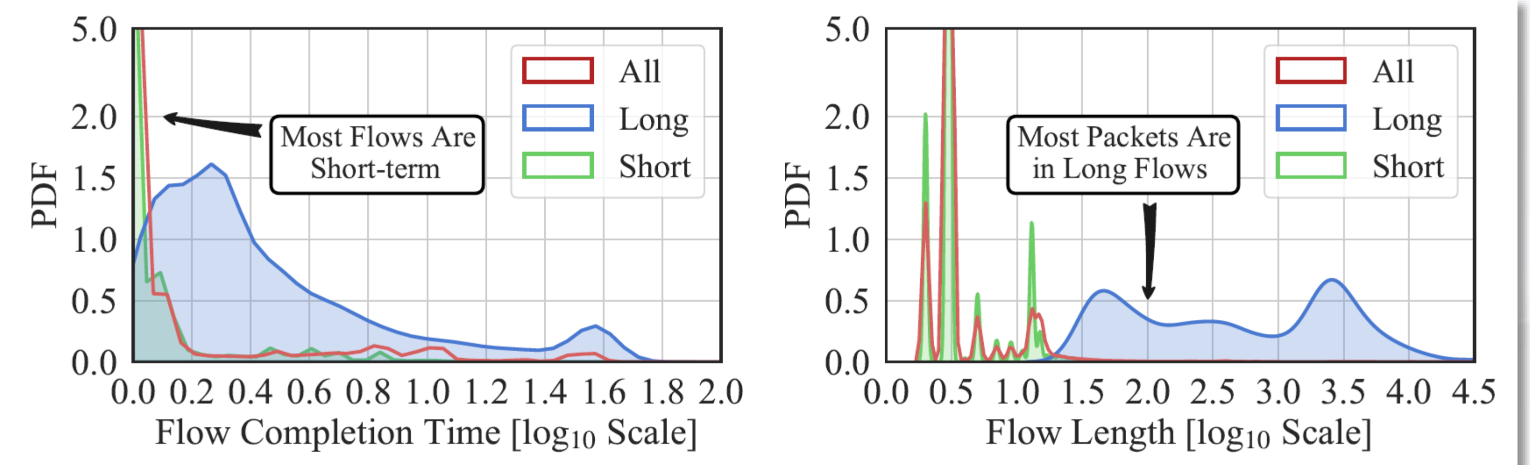
  - How to reduce the density of a graph?

Graph Before Density Reduction



3. Design: How to reduce the graph density?

- Observation: most flows are short flow, and most packets are in long flow.
- Solution: we construct edges to represent short and long flow, separately.



(a) FCT distribution. (b) Flow length distribution.

3. Design: How to reduce the dense graph?

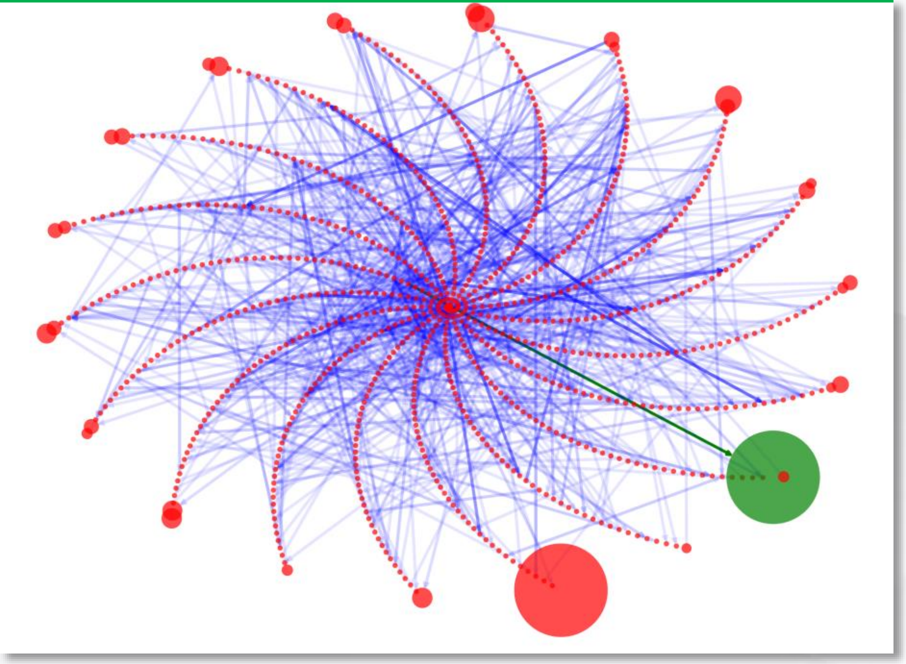
- Many short flows are similar, e.g., DNS queries, password cracking.
  - We aggregate the short flows and use one edge to represent many short flows

- Long flows have complex patterns.
  - We extract fine-grained features for long flows, i.e., distribution features.

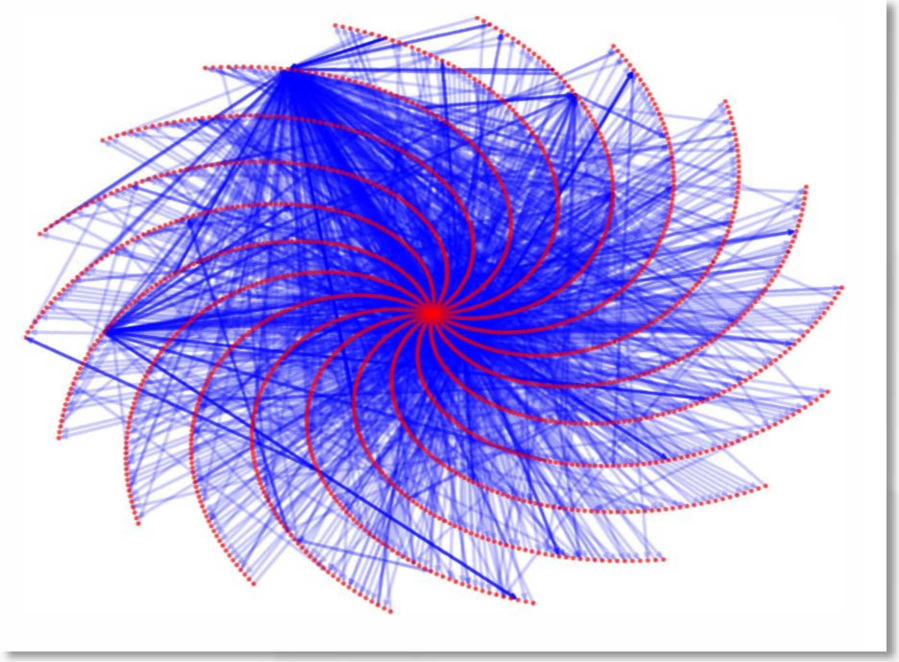
- One edge → many short flows or one long-flow.
- One vertex → a group of addresses or one address.

3. Design: How to reduce the dense graph?

Graph After Density Reduction



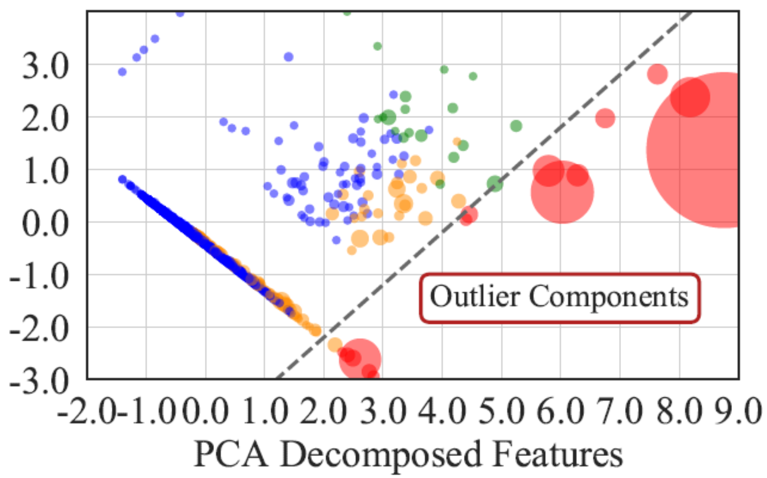
Graph Before Density Reduction



3. Design: How to efficiently identify attack traffic?

- The size of graph is still too large for real-time graph learning.

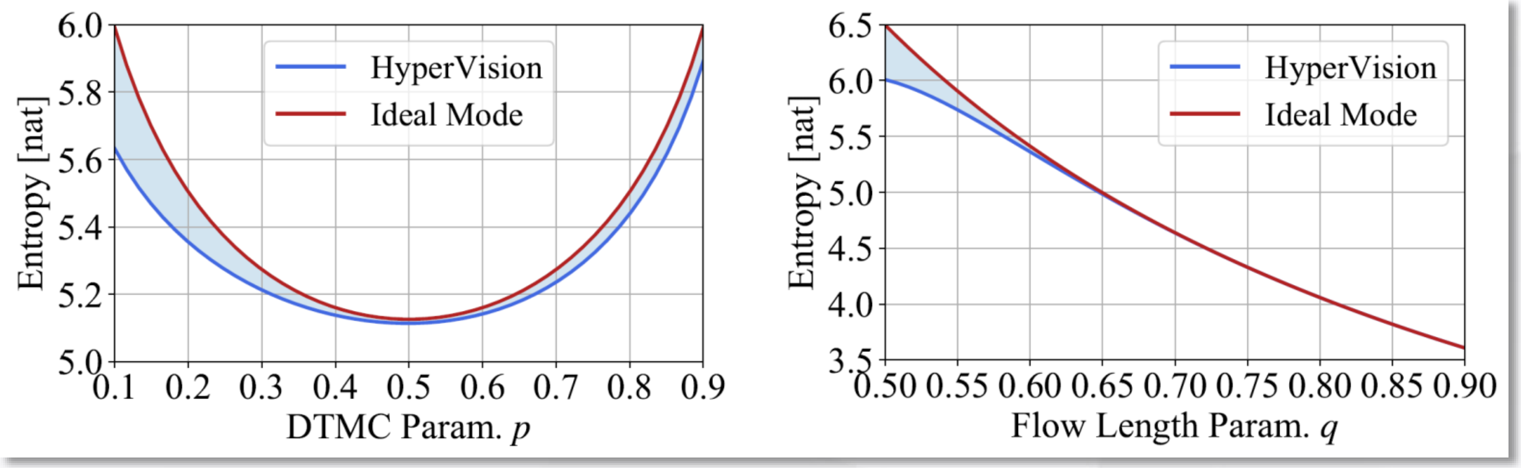
- We exclude benign components by clustering the high-level statistics.



(b) Scatter of the components.

4. Theoretical Analysis

- To prove the effectiveness of the method, we developed an information theory based analysis framework, which models flows by using DTMC.
- By calculating the entropy of the DTMC, we prove the amount of information preserved on the graph is near-optimal.



5. Experimental Analysis: Setup

- We implement our method using Intel DPDK (Data Plane Development Toolkit).
  - *The source code is publicly available.*

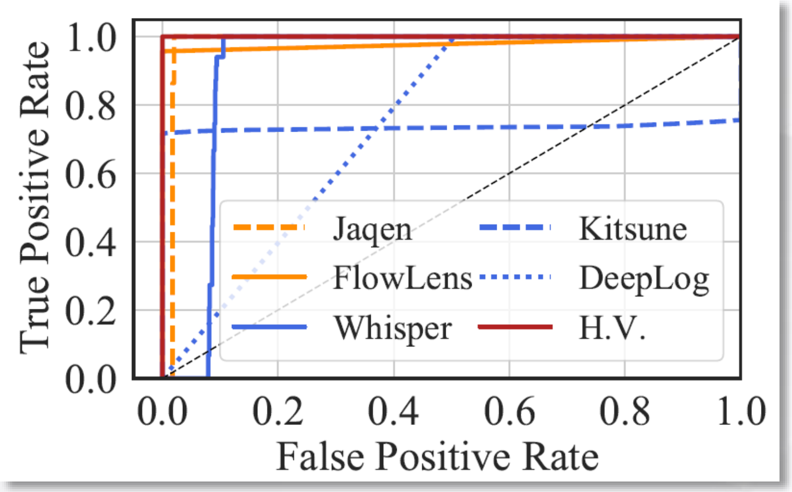
- On the physical testbed, we replay 92 kinds of malicious traffic, including 48 attacks with encrypted malicious traffic:
  - *Traditional brute attacks* (e.g., amplification attacks).
  - *Encrypted flooding traffic* (e.g., the Crossfire Attack).
  - *Encrypted Web attack traffic* (e.g., CVE-2013-2028).
  - *Malware generated traffic* (e.g., C&C Channel).

- These attack traffic is collected form a scaled private cloud network (> 1500 users), and the malware traffic is manually extracted form public datasets.

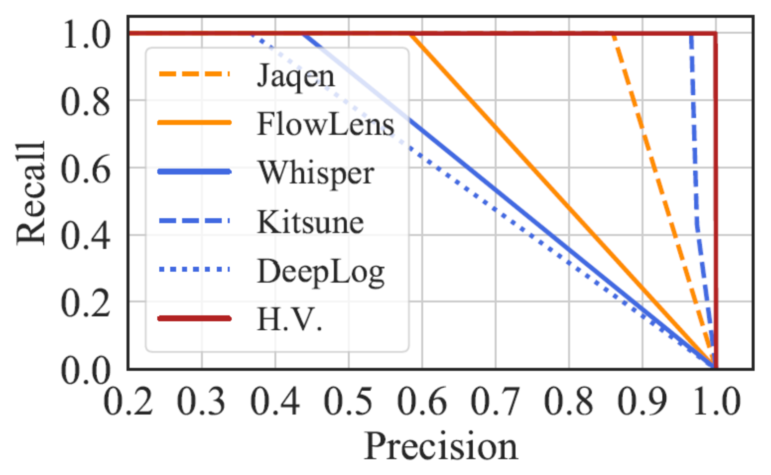
5. Experimental Analysis: Results

- HyperVision outperforms 5 SOTA methods in detection accuracy.
  Over 50% of the stealthy attacks cannot be identified by all the methods.

ROC Comparison

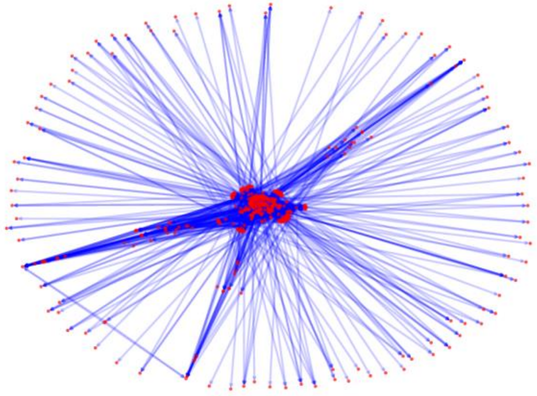


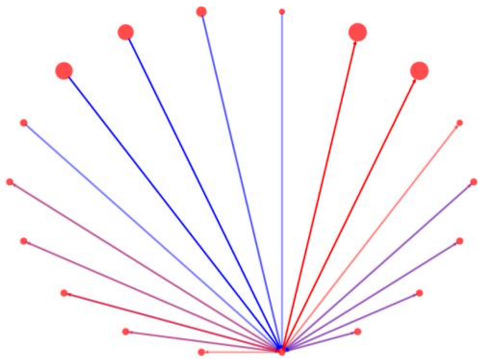
PRC Comparison

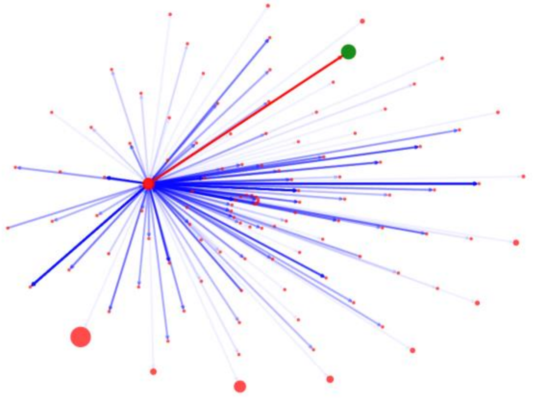


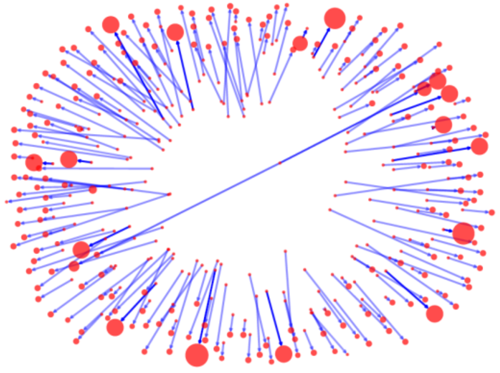
5. Experimental Analysis: results

- The method can detect many sophisticated attacks.


(a) Crossfire.

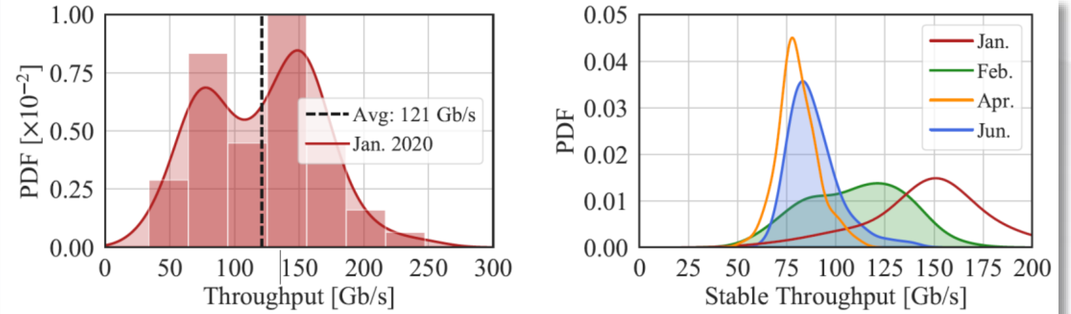

(b) SSH cracking.


(c) XSS detection.

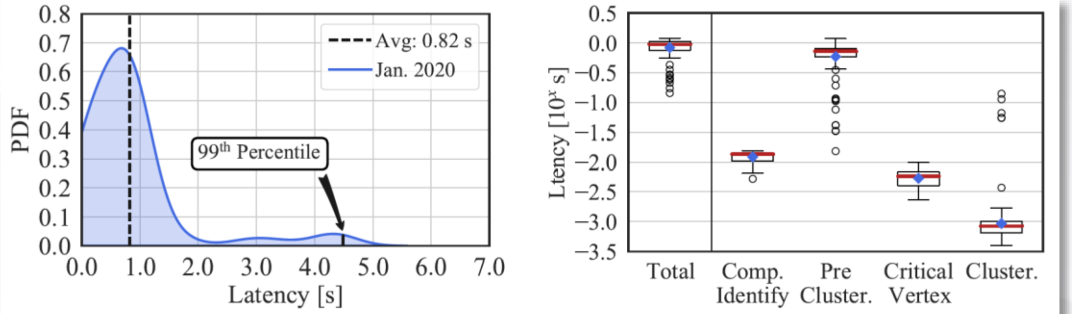

(d) P2P botnet.

5. Experimental Analysis: results

- The method realizes both high detection throughput and low latency.
  - The graph detection module can process 121 Gb/s traffic on average.
  - Meanwhile, the average detection latency is only 0.82s.



(c) Graph detection throughput. (d) Stable detection throughput.

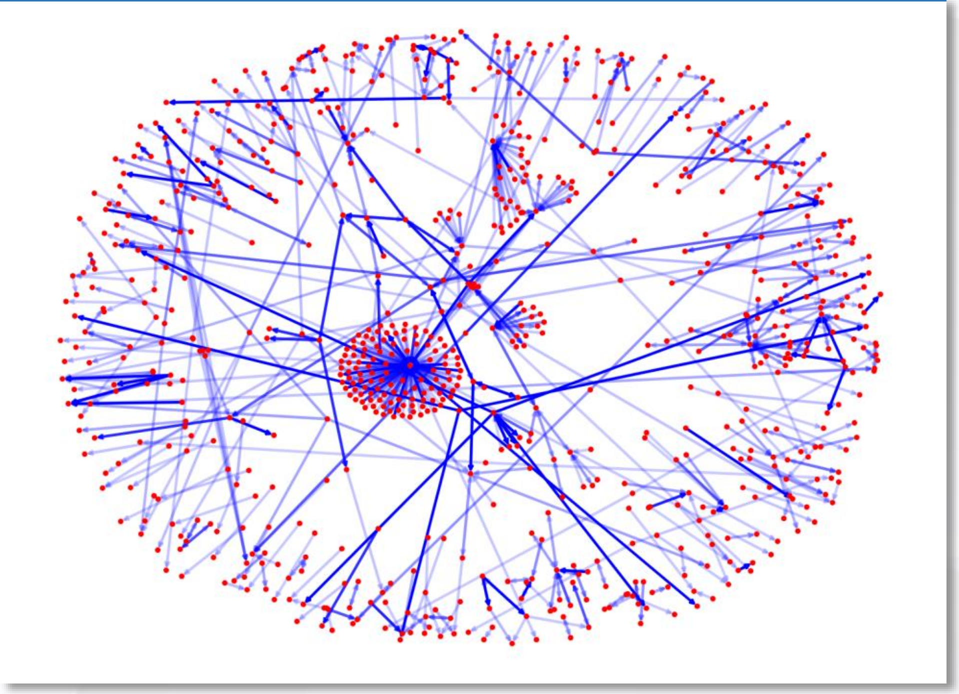


(c) Graph detection latency. (d) Detection latency composition.

6. Conclusions and Takeaways

- We develop an encrypted malicious traffic detection method, which utilize *flow interaction patterns* represented by *graph structural features*.

Flow Interaction Graph



6. Conclusions and Takeaways

- Many attack traffic generates benign traffic features, e.g., packet rates.
- Design new traffic features to tackle this issue.
- The idea of using the graph is derived from provenance graph analysis.

We believe the flow interaction graph can be applied to other network applications.

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