

SIAMHAN: IPv6 Address Correlation Attacks on TLS Encrypted Traffic via Siamese Heterogeneous Graph Attention Network



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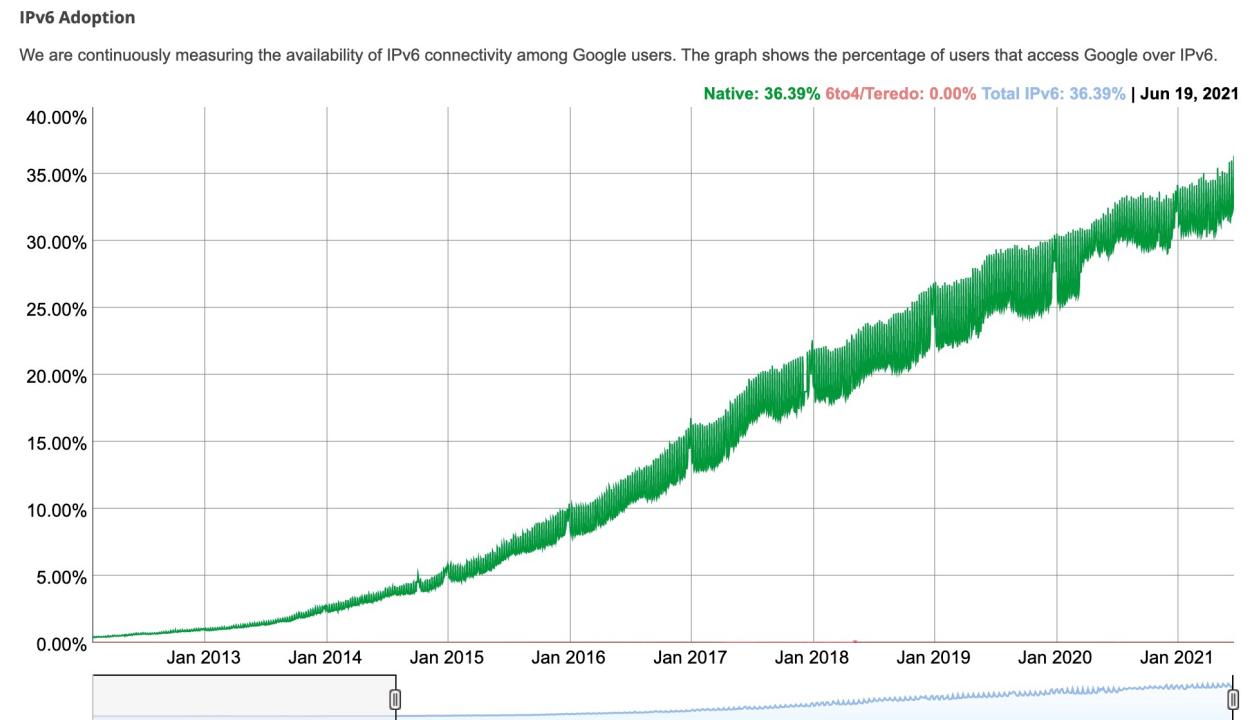
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IPv6 Networks

The Growth of IPv6 Networks

- An increasing number of network providers expediting the deployment of IPv6
- One-third of Internet users can now access online services through IPv6
- Increased focus on IPv6 security and privacy issues



Don't Forget to Lock the Back Door!
A Characterization of IPv6 Network Security Policy
Towards A User-Level Understanding of IPv6 Behavior
Who Knocks at the IPv6 Door? Privacy is Not an Option:
Detecting IPv6 Scanning Attacking the IPv6 Privacy Extension

Flaw Label: Exploiting IPv6 Flow Label

Security and Privacy Considerations for
IPv6 Address Generation Mechanisms

IPv6 User Activity Correlation

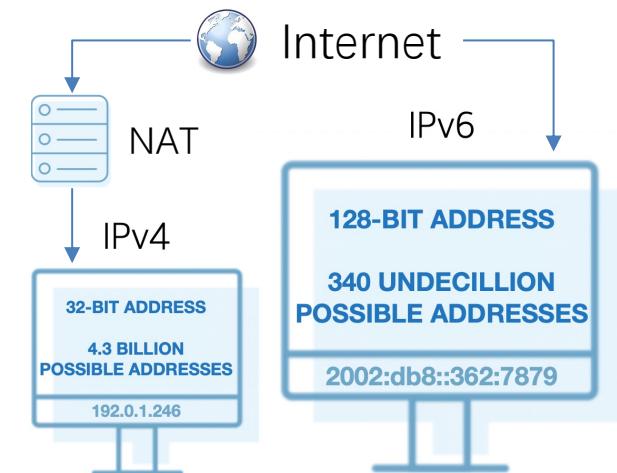
User Activity Correlation

- Leveraging traffic meta-information to identify and track users
- Could work even on traffic encrypted by **Transport Layer Security (TLS)**



Work on IPv6

- Unlike IPv4 - rare deployment of **Network Address Translation (NAT)**
- An IPv6 address usually corresponds to one single user
- **Serious individual-level privacy threat!**



Limitation

Address-based Correlation

- Associating an IPv6 address with a user's activity
- Weak configuration - a **CONSTANT** interface identifier:

2001:db8::face:b00c:0:a7 → 2001:db8::face:b00c:0:a7

- **Mitigation** - temporary addresses (RFC 4941):

2001:db8::7c61:2880:3148:36e1 → 2001:db8::6efb:720a:8321:92dc
Dynamic changing and pseudorandom

Traffic Characteristic Correlation

- Associating traffic with a user's activity
- Analyzing the patterns in the encrypted traffic
- **Limitation** - **closed-world** dataset:

Can only correlate the traffic of a selected subset of users (**only known users**)

IPv6 Address Correlation Attack

Challenge

Frequently changing client addresses
Widespread payload encryption with TLS

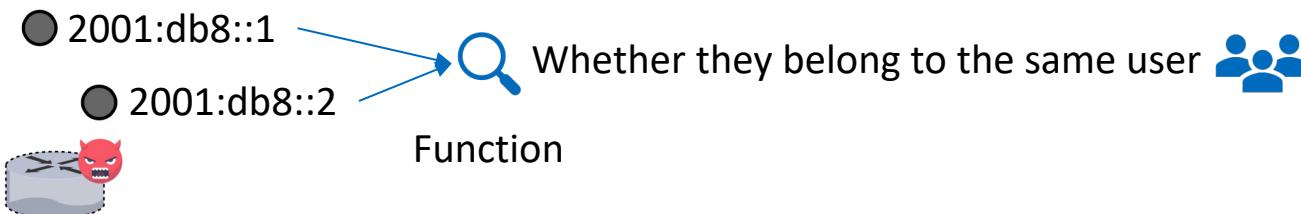


Making address-to-user correlation unreliable

Our Attack

Learning a correlation function from TLS encrypted traffic

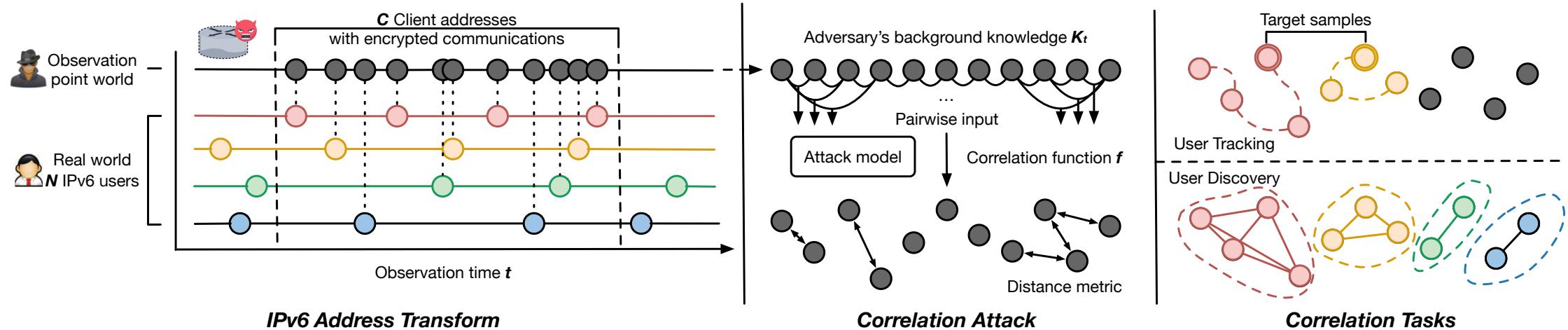
Two arbitrary addresses



2-step attack:

- Construct **knowledge graph** for each client address
- Capture the relationship between each two addresses with an **attack model**

Threat Model



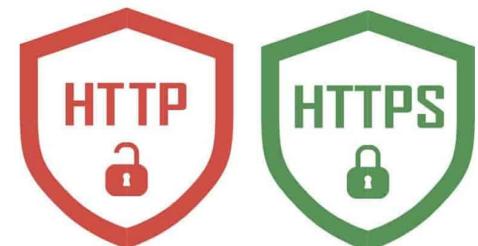
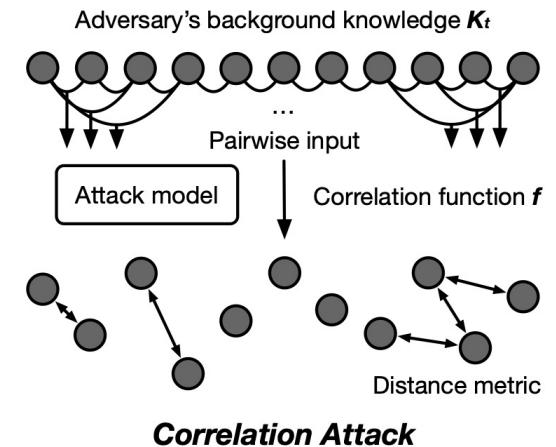
Attack Scenario

- An observation point for wiretapping
- **Adversary's background knowledge K_t :**
 - Encrypted communication behavior of all IPv6 addresses during the wiretapping time t
- **Correlation function f :**
 - Judging the relationship of a pair of addresses
 - Learned by an attack model - distance metric with a threshold η

Adversary Ground Truth

Labeling Trick

- Leaked persistent cookie
 - A few users use the changing addresses and access some websites without HTTPS deployment
 - The TLS connections of these addresses could be labeled
- The adversary could perform large-scale correlation attacks on the wild TLS traffic without plaintext once obtaining the model



SiamHAN

Knowledge Graph

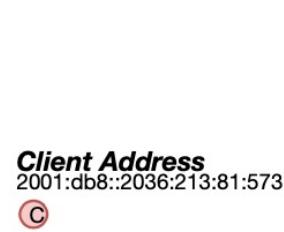
Heterogeneous graph - **multi-type** nodes and neighbor relationships

Node and Node Attribute

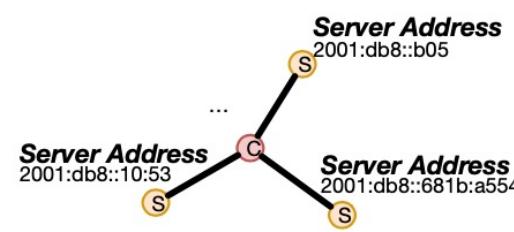
- **Client node C**
 - The 32-digit hexadecimal IPv6 client address
 - Each graph only have one
- **Server node S**
 - The 32-digit hexadecimal IPv6 server address who have established TLS communications with the client
- **Fingerprint node F**
 - Field values of the **ClientHello**, **ServerHello**, **Certificate** messages, and statistical characteristics
 - **Client fingerprints** and **server fingerprints**

Node Type	Source	Label	Node Attribute
Client node	IPv6 header	C	Client address
Server node	IPv6 header	S	Server address
Client fingerprint	ClientHello	F_1	Record version
		F_2	Client version
		F_3	Cipher suites
		F_4	Compression
Server fingerprint	ClientHello	F_5	SNI
		F_6	Record version
		F_7	Server version
		F_8	Cipher suite
Certificate	ServerHello	F_9	Algorithm ID
		F_{10}	Issuer
		F_{11}	Subject
		F_{12}	Date statistics
		F_{13}	First connection
			Count statistics

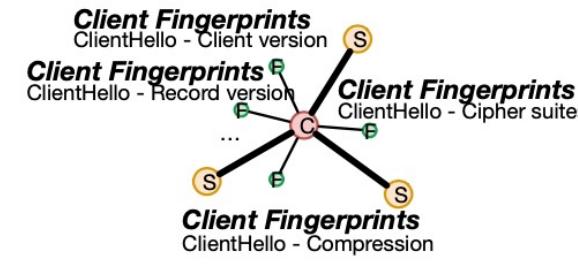
SiamHAN



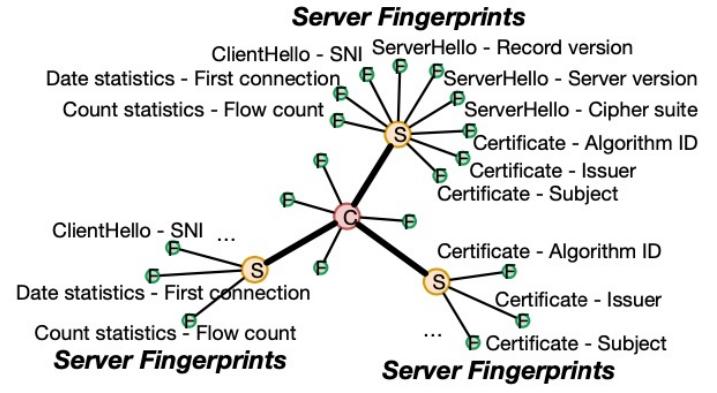
(a) Node **C**



(b) Nodes **S** and **SCS** meta-paths



(c) Nodes **F** and **FCF** meta-paths



(d) Nodes **F** and **FSF** meta-paths

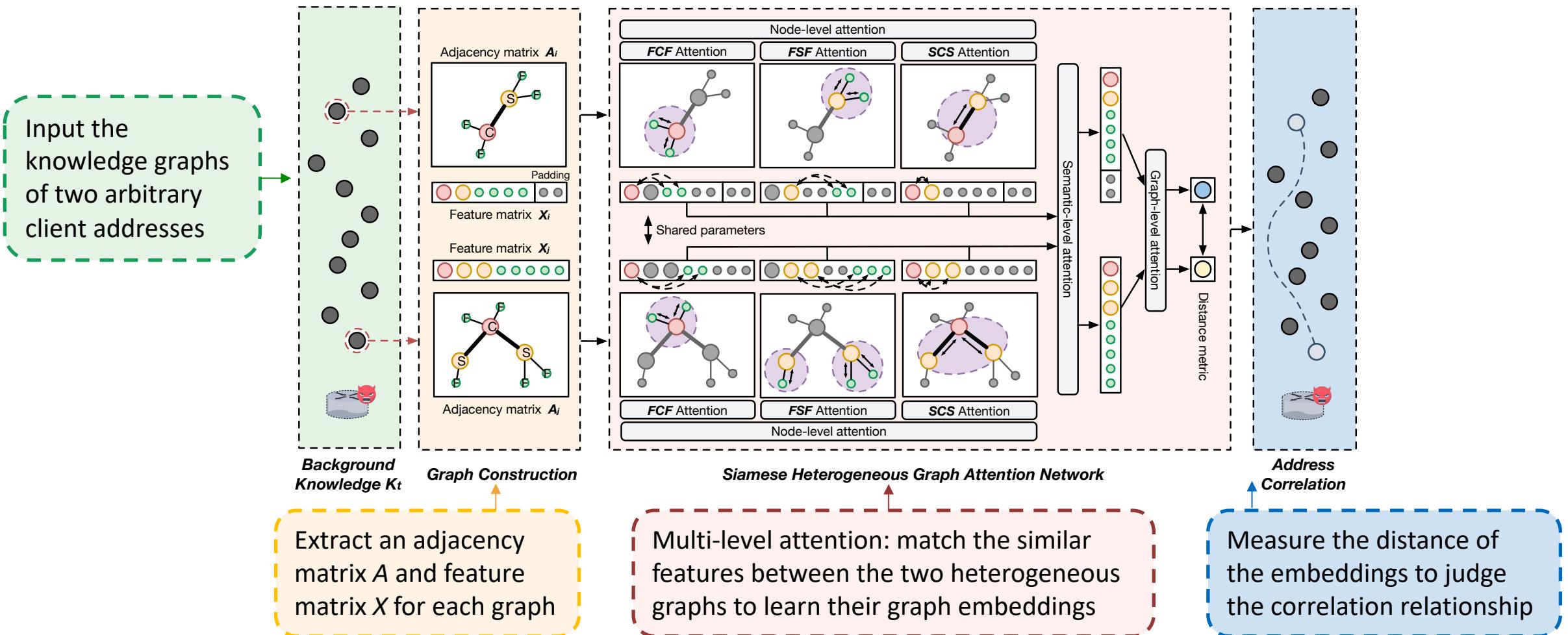
Knowledge Graph

Neighbor Relationship

- **SCS meta-path** - Connecting **C** and **S**
 - The **TLS communication activities** between the client and multiple servers
- **FCF meta-path** - Connecting **C** and client fingerprint **F**
 - The **browser parameters** that may be used behind the client
- **FSF meta-path** - Connecting **S** and server fingerprint **F**
 - The **service characteristics** behind each server

SiamHAN

Model Architecture



SiamHAN

Model Architecture

Node-level attention

- Learning the importance of meta-path-based neighbors and aggregating them to get the **semantic-specific node embeddings (SCS FCF FSF)**

Locally match similar nodes in each single meta-path-based semantic

Semantic-level attention

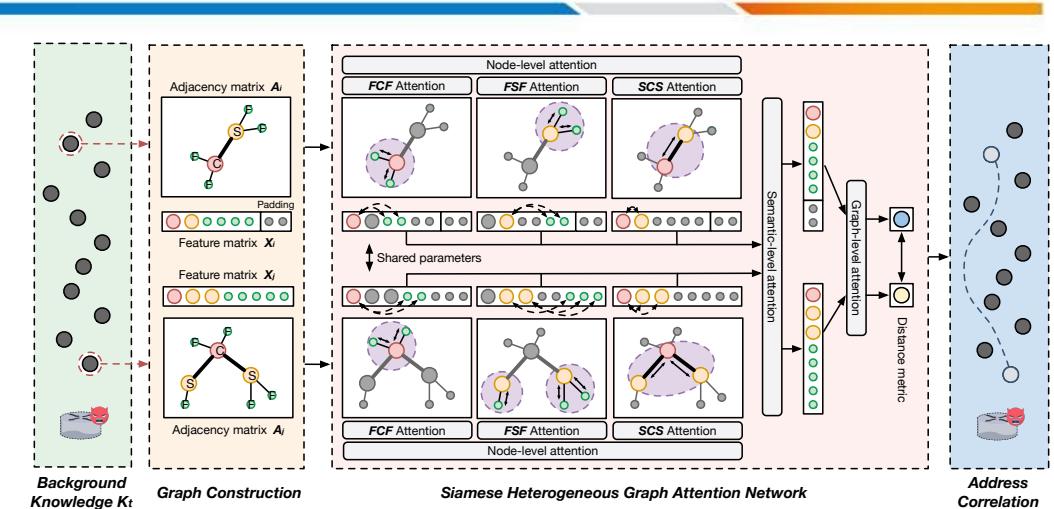
- learning the importance of three types of semantic-specific embeddings for each node and fusing them as **comprehensive node embeddings**

Semantic aggregation

Graph-level attention

- aggregating the comprehensive embeddings of all nodes in the knowledge graph to get the **graph embedding**

Globally match similar nodes



Metric learning with Siamese Network

- Measuring the **distance D** between the two graphs and judging the correlation **relationship R** through a **threshold η**

$$D = \|Z_1 - Z_2\|_2,$$

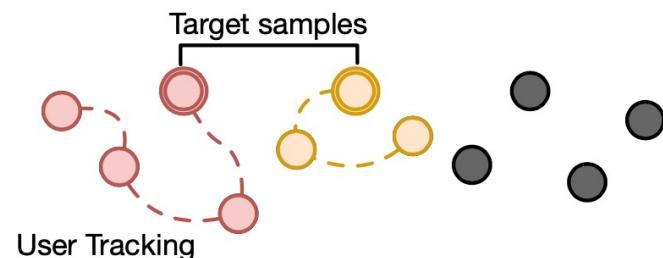
$$R = \begin{cases} 1 & D < \eta \\ 0 & D \geq \eta \end{cases},$$

- Contrastive loss function

$$L = Y \cdot D^2 + (1 - Y) \{\max(0, m - D)\}^2$$

SiamHAN - User Tracking

User Tracking Task



Searching all addresses correlated to the address sample of target users

- Target users' one client address activity is known
- The adversary could compute the relationship between **each target address** and **each test address** during the observation

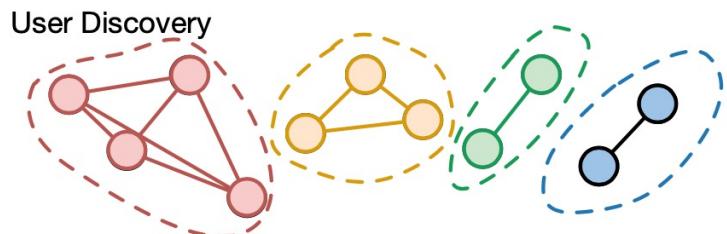
Algorithm 1 The tracking algorithm applied by SIAMHAN

Require: Pre-trained SIAMHAN ρ ; Tracking candidate set S ; Test address set T ; Background knowledge κ_t .
Ensure: Address sets T_{S_i} link to the same user with each S_i

```
1: for  $S_i$  in tracking candidate set  $S$ , where  $i \leq |S|$  do
2:   Initialize target address set  $T_{S_i} = \{\}$ 
3:   for  $T_j$  in test address set  $T$ , where  $j \leq |T|$  do
4:     Build pairwise knowledge graphs for  $\langle S_i, T_j \rangle$ 
5:     Test relationship  $R$  of  $\langle S_i, T_j \rangle$  using pre-trained  $\rho$ 
6:   end for
7:   Append  $T_j$  in address set  $T_{S_i}$  if relationship  $R = 1$ 
8: end for
9: return  $T_{S_i}$  for each  $S_i$ 
```

SiamHAN - User Discovery

User Discovery Task



Calculating the correlation between every two addresses to acquire address clusters

- The number of users in traffic is unknown
- The adversary could use a recursion algorithm to determine the unique users

Algorithm 2 The discovery algorithm applied by SIAMHAN

Require: Pre-trained SIAMHAN ρ ; Discovery candidate set S ; Background knowledge κ_t ; Task threshold η .

Ensure: User groups G under the discovery candidate set S

```
1: Build knowledge graphs for each  $S_i$ 
2: Initialize user group set  $G = \{G_1\}$ 
3: Initialize  $S_1$  into the first user group  $G_1$ 
4: for  $S_i$  in discovery candidate set  $S$ , where  $1 < i \leq |S|$  do
5:   for  $G_k$  in user group set  $G$  do
6:     for Address  $S_j$  in group  $G_k$ , where  $j \leq |G_k|$  do
7:       Calculate distance  $D$  for  $\langle S_i, S_j \rangle$  using  $\rho$ 
8:     end for
9:     Calculate average distance  $\bar{D}_k$  for  $S_i$  to  $G_k$ 
10:    end for
11:    if All group average distance  $\bar{D}_k > \eta$  then
12:      Initialize a new user group  $G_{|G|+1}$  into  $G$ 
13:      Initialize  $S_i$  into the new user group  $G_{|G|+1}$ 
14:    else
15:      Classify  $S_i$  into  $G_k$  with the minimum  $\bar{D}_k$ 
16:    end if
17:  end for
18: return User group set  $G$ 
```

Evaluation - Dataset

Dataset Composition

- Passively collected on China Science and Technology Network (CSTNET) from March to July 2018
- Labeling - persistent cookie
- 1.7k IPv6 users with TLS traffic

AS Name	% Hits	Device OS	% Hits	SNI	% Hits	TLS Field	% Hits
CSTNET	78.6%	Windows	63.7%	*.google.com	17.9%	Record version	93.1% / 93.9%
China Unicom	10.1%	Android	23.7%	*.adobe.com	11.6%	Client version	93.1%
CNGI-CERNET2	4.0%	iOS	6.2%	*.microsoft.com	11.2%	Server version	93.9%
CERNET	2.4%	Linux	5.0%	*.gstatic.com	4.8%	Cipher suites	93.1% / 93.9%
Reliance Jio	1.6%	Mac OS X	1.3%	*.macromedia.com	3.3%	Compression	93.1%
Cloudflare	0.8%	BlackBerry	0.1%	*.cloudflare.com	2.4%	SNI	93.1%
PKU6-CERNET2	0.5%	Chrome OS	0.1%	*.2mdn.net	1.9%	Algorithm ID	78.4%
TSINGHUA6	0.5%	Symbian OS	0.1%	*.xboxlive.com	1.6%	Issuer	78.4%
ZSU6-CERNET	0.4%	Firefox OS	0.1%	*.xhcdn.com	1.2%	Subject	78.4%

Time-based Data Split

- Realistic setting from an adversary
 - First 3-month data for training
 - The 4th month's data for validation
 - The 5th month's data for test

Entity	Training	Validation	Test
User	1.0k	0.2k	0.5k
Sample Pair	1.2M	0.1M	0.2M
Knowledge	3 months	1 month	1 month

Evaluation - Baselines and Metrics

Baselines

User IP Profiling¹ - building **user profiles** through all the destination IPs of the client address and using a Bayesian classifier

User SNI Profiling² - using the SNIs in all the TLS ClientHello messages from the client as a **user profiles** and using a Bayesian classifier

Client Fingerprinting³ - extracting the fields of the TLS ClientHello message as the user's **client fingerprints** and using a Random Forest classifier

Deepcorr⁴ - using the **flow sequence** characteristics to achieve correlation tasks with a deep learning model

Metrics

- True Positive Rate (TPR)
- False Positive Rate (FPR)
- Area Under Curve (AUC)
- Accuracy
 - Tracking Accuracy (TA)
 - Discovery Accuracy (DA)

[1] Marek Kumpost and Vashek Matyas. User profiling and re-identification: Case of university-wide network analysis. In *TrustBus*, pages 1–10, 2009

[2] Roberto Gonzalez, Claudio Soriente, and Nikolaos Laoutaris. User profiling in the time of HTTPS. In *IMC*, pages 373–379, 2016

[3] Blake Anderson and David A. McGrew. OS fingerprinting: New techniques and a study of information gain and obfuscation. In *CNS*, pages 1–9, 2017

[4] Milad Nasr, Alireza Bahramali, and Amir Houmansadr. DeepCorr: Strong flow correlation attacks on tor using deep learning. In *CCS*, pages 1962–1976, 2018

Evaluation - Analysis of Hierarchical Attention

Analysis of Node-level Attention

High attention value of node C

- Matching the same constant IID in the two client addresses

High attention value of node S or F

- Matching the common server address or fingerprints

Analysis of Semantic-level Attention

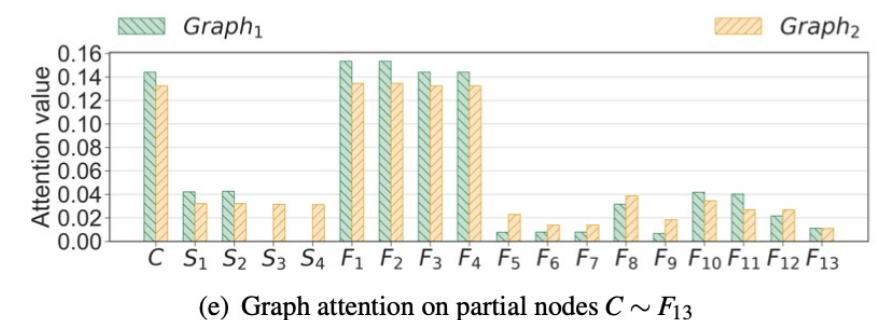
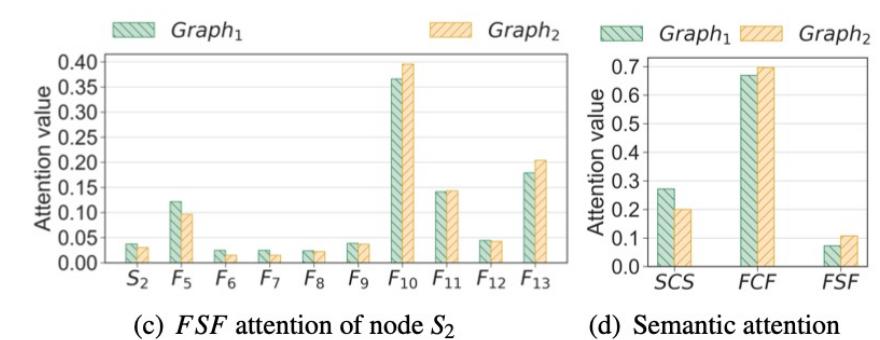
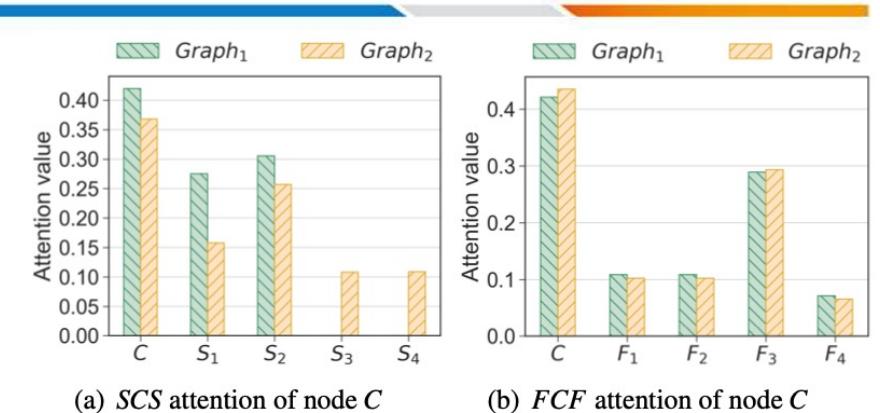
High attention value of FCF meta-path

- Learning user browser parameters is more important

Analysis of Graph-level Attention

$F_1 \sim F_4$ - Client Fingerprints; $F_5 \sim F_{13}$ - Server Fingerprints

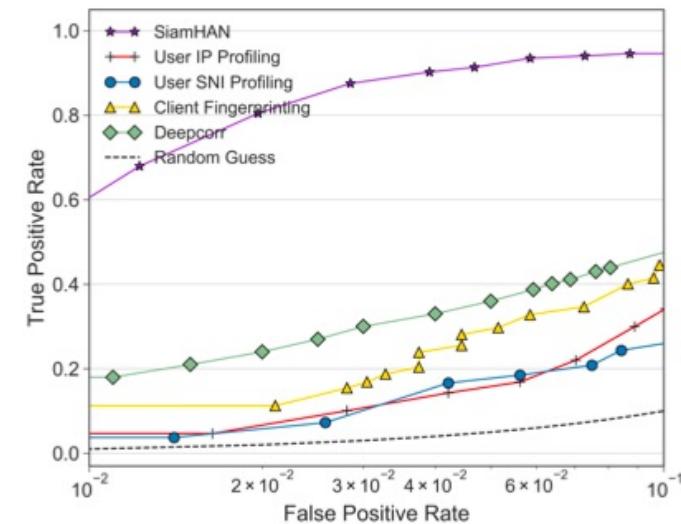
- Taking more attention to the client meta-information than the server meta-information



Evaluation - Address Correlation

Correlation Performance

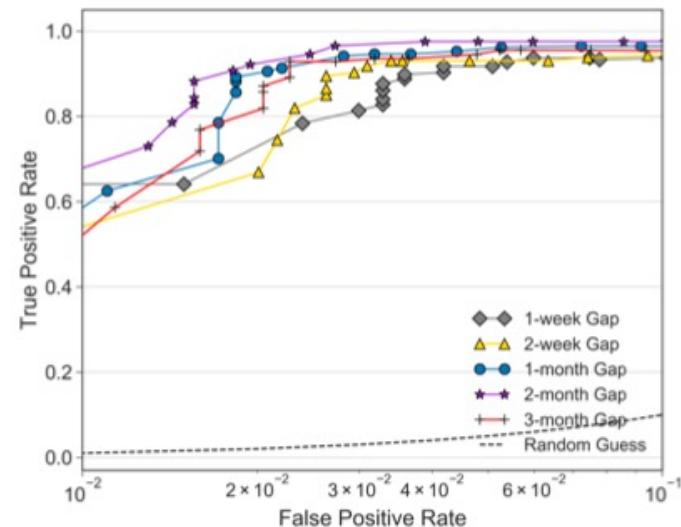
For a target $FPR = 4 \times 10^{-2}$, while SiamHAN achieves a TPR of 0.90, all baselines provide TPRs less than 0.40



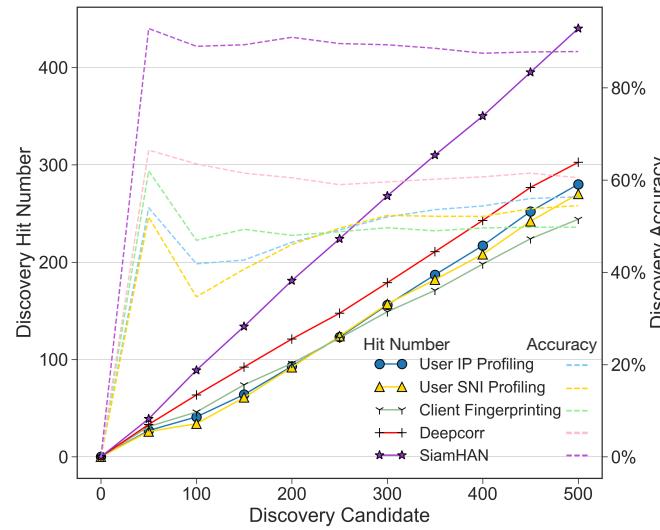
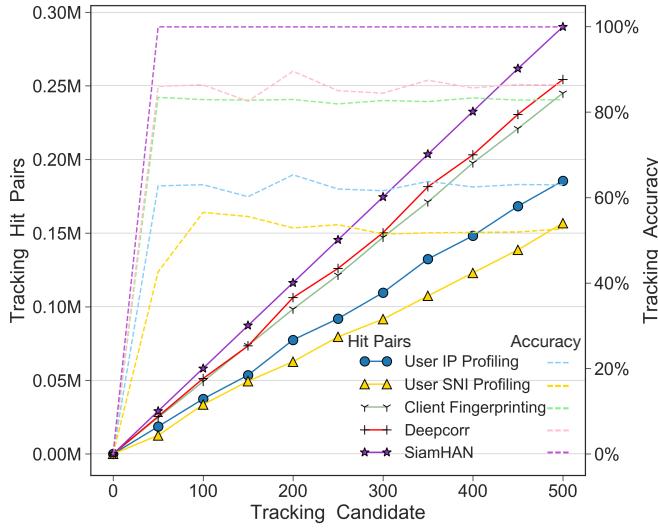
Timeliness

Evaluating on the **different time gaps** between training and test

For a target $FPR = 10^{-1}$, under all time gaps, SiamHAN provides TPRs more than 0.95



Evaluation - User Tracking and User Discovery



SiamHAN outperforms existing correlation techniques with **99%** and **88% accuracy** compared to **85%** and **60% accuracy** of the best baseline on the **user tracking** and **user discovery** task

SiamHAN could achieve **1.10~1.19** and **1.40 ~ 1.54** times more hit than Deepcorr

Conclusion

- We explore the implementation of **user activity correlation** on IPv6 networks.
- We propose **IPv6 address correlation attacks**, which leverage an attack model SiamHAN to learn the correlation relationship between two arbitrary IPv6 addresses based on the background knowledge of TLS traffic.
- We hope that our work demonstrates the **serious threat** of IPv6 address correlation attacks and calls for **effective countermeasures** deployed by the IPv6 community.

THANK YOU FOR LISTENING

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