

Multi-domain Anomaly Detection in 5G Networks through Continuous Dynamic Graphs

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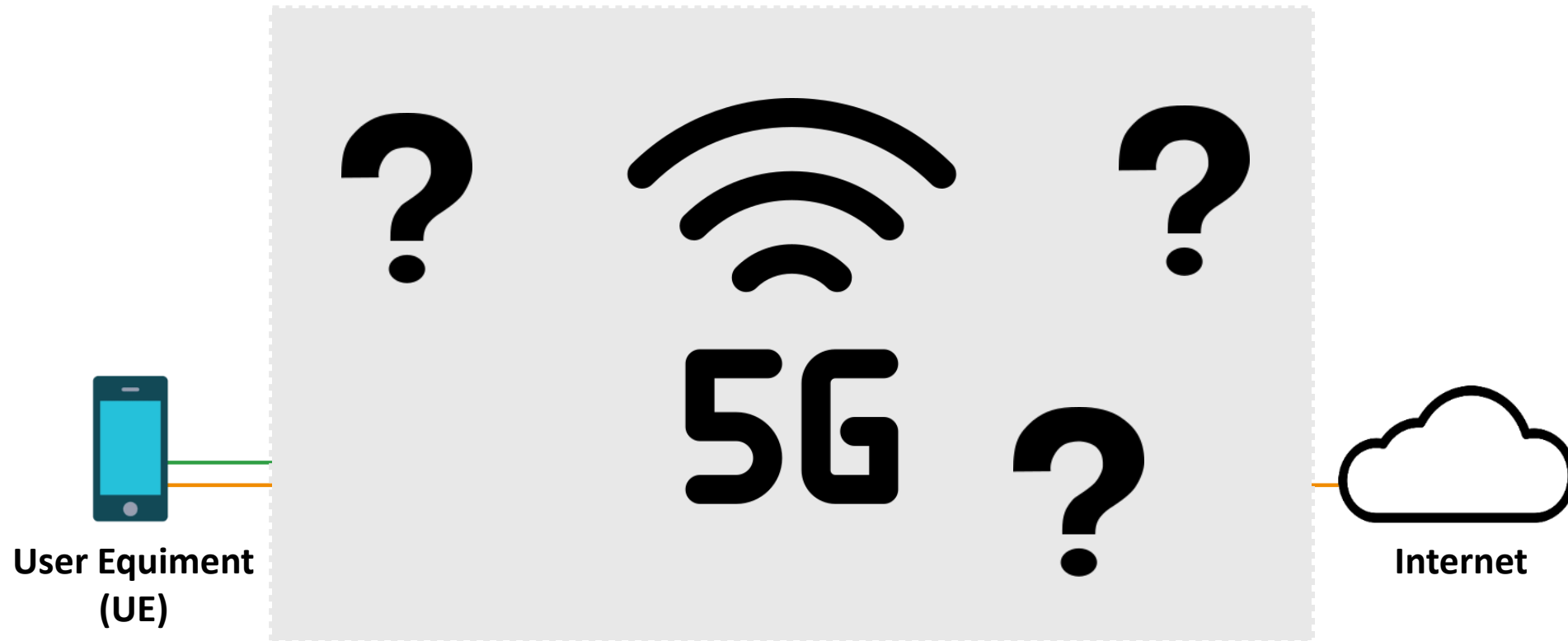
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3. **Detection State of The Art**
4. **Proposing a new formalization**
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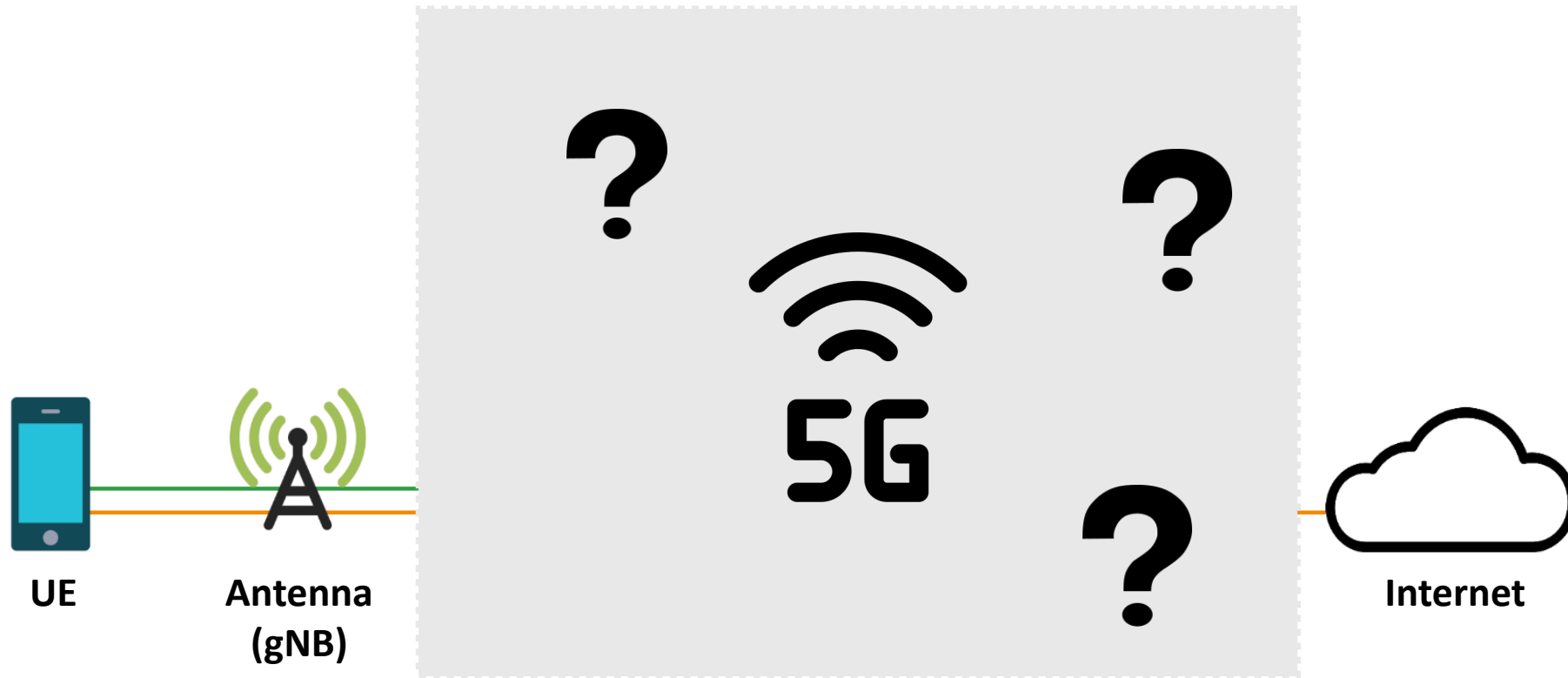
What is 5G?

A brief introduction

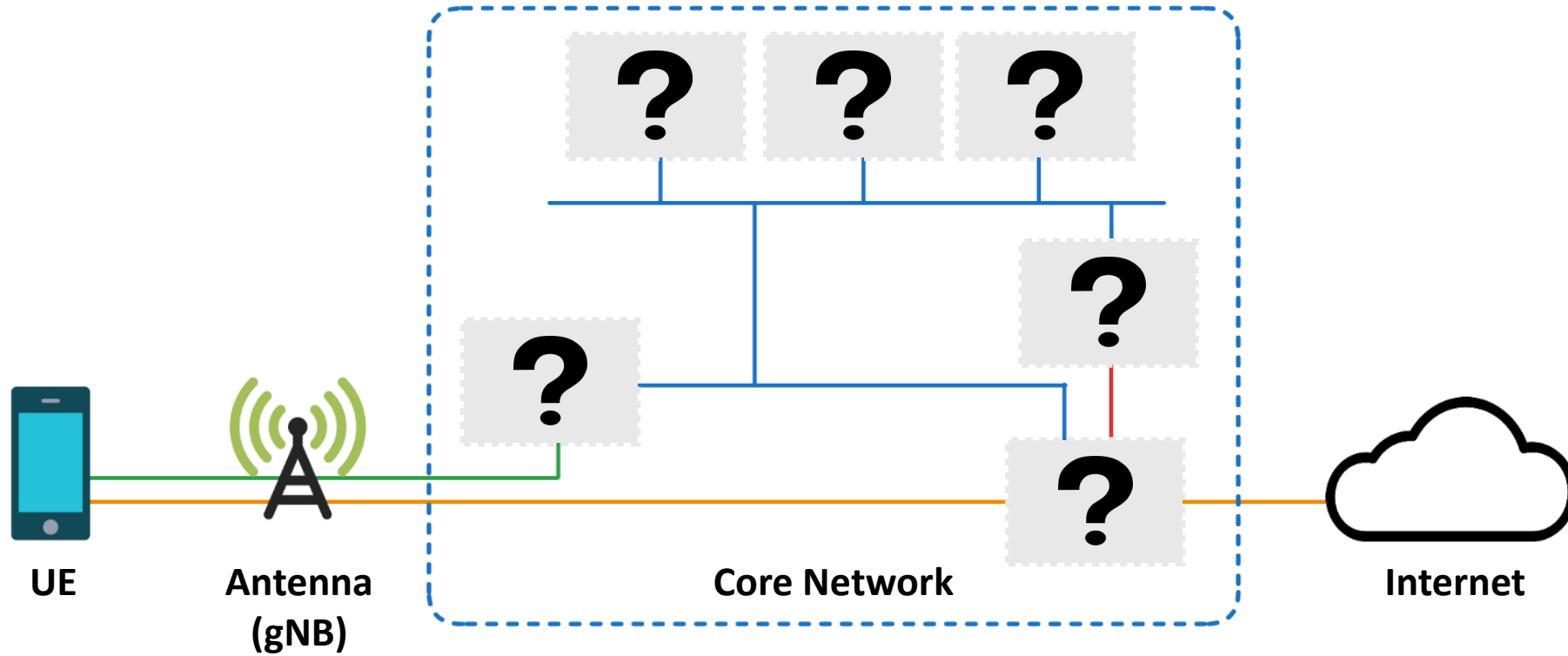
What is 5G ?



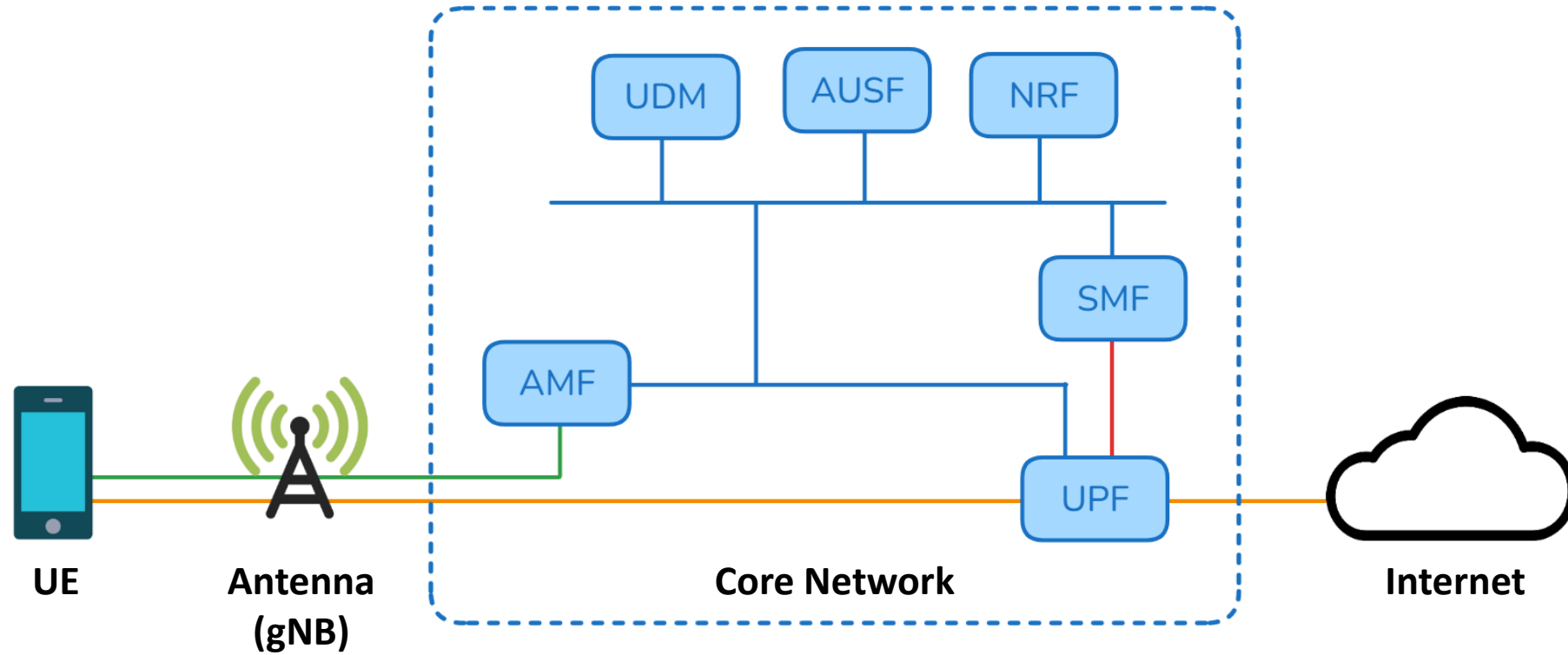
What is 5G ?



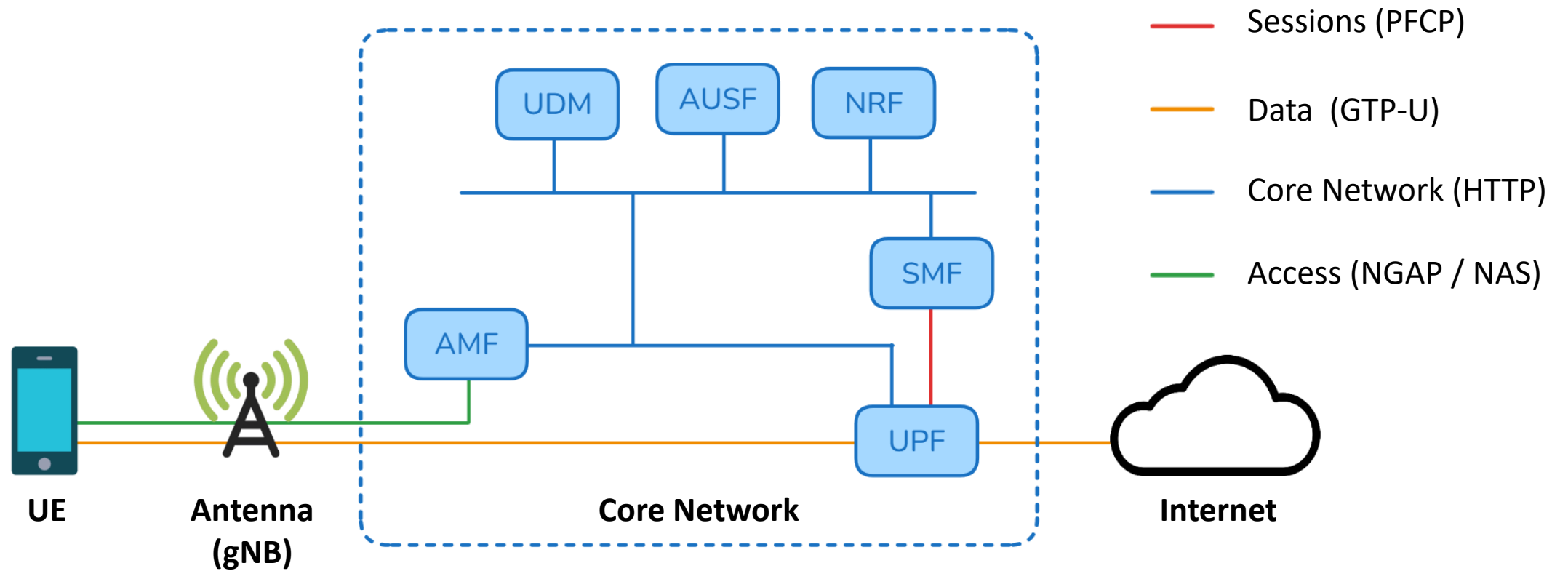
What is 5G ?



What is 5G ?

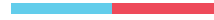


What is 5G ?

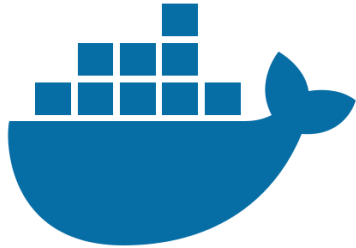


Channels with their own role and protocol stacks

Major changes from 4G

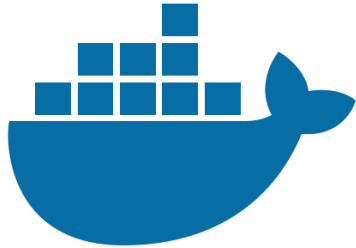


Network Function Virtualization (NFV)



Major changes from 4G

**Network Function
Virtualization (NFV)**

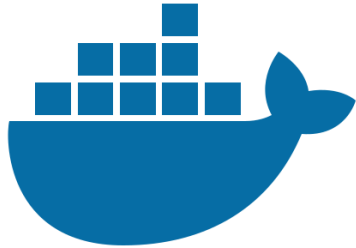


**Software Defined
Network (SDN)**



Major changes from 4G

**Network Function
Virtualization (NFV)**



**Software Defined
Network (SDN)**

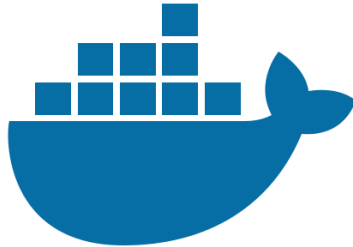


**Service-Based
Interfaces (SBI)**



Major changes from 4G

**Network Function
Virtualization (NFV)**



**Software Defined
Network (SDN)**



**Service-Based
Interfaces (SBI)**

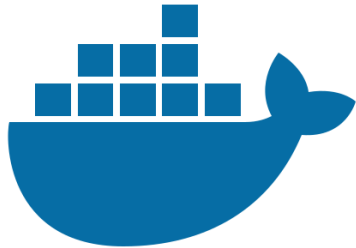


5G networks increasingly resemble distributed systems in their design

What about the attacks ?

Few examples of attacks now possible in 5G

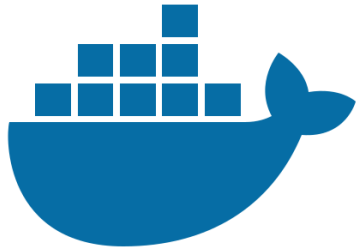
Broader attacking surface



VM/Docker escape [1]

[1] A. Tomar, D. Jeena, P. Mishra, et R. Bisht, « Docker Security: A Threat Model, Attack Taxonomy and Real-Time Attack Scenario of DoS », in *2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, janv. 2020, p. 150-155. doi: [10.1109/Confluence47617.2020.9058115](https://doi.org/10.1109/Confluence47617.2020.9058115).

Broader attacking surface



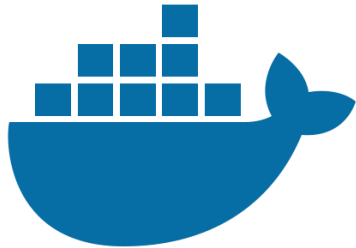
VM/Docker escape [1]



Man in the Middle [2]

[2] T. Hoger, P. Owezarski, et G. Durand-Nauze, « Control Traffic Dataset and Generation Framework for 5G Networks ». 27 février 2026. doi: [10.5281/zenodo.15853959](https://doi.org/10.5281/zenodo.15853959).

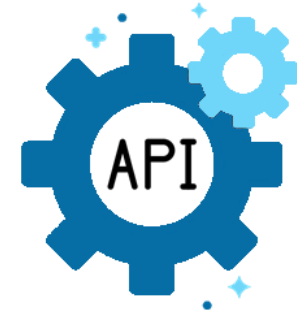
Broader attacking surface



VM/Docker escape [1]



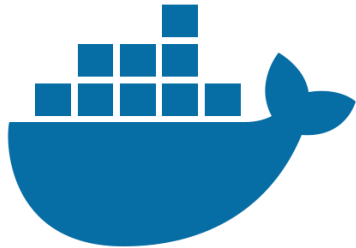
Man in the Middle [2]



Fuzzing [2]

[2] T. Hoger, P. Owezarski, et G. Durand-Nauze, « Control Traffic Dataset and Generation Framework for 5G Networks ». 27 février 2026. doi: [10.5281/zenodo.15853959](https://doi.org/10.5281/zenodo.15853959).

Broader attacking surface



VM/Docker escape [1]



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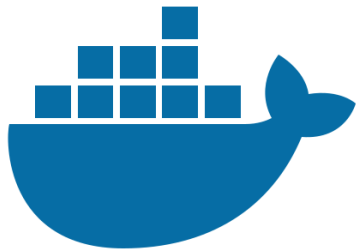
Fuzzing [2]



Slice pivoting [3]

[3] A. Kumar et V. L. L. Thing, « Malicious Lateral Movement in 5G Core With Network Slicing And Its Detection », in *2023 33rd International Telecommunication Networks and Applications Conference*, nov. 2023, p. 110-117. doi: [10.1109/ITNAC59571.2023.10368559](https://doi.org/10.1109/ITNAC59571.2023.10368559).

Broader attacking surface



VM/Docker escape [1]



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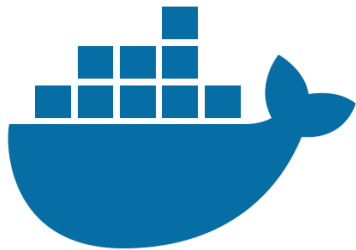
Slice pivoting [3]



Supply Chain Backdoor [4]

[4] R. G. Kula, D. M. German, A. Ouni, T. Ishio, et K. Inoue, « Do Developers Update Their Library Dependencies? An Empirical Study on the Impact of Security Advisories on Library Migration », *Empir Software Eng*, vol. 23, n° 1, p. 384-417, févr. 2018, doi: [10.1007/s10664-017-9521-5](https://doi.org/10.1007/s10664-017-9521-5).

Broader attacking surface



VM/Docker escape [1]



Man in the Middle [2]



Fuzzing [2]



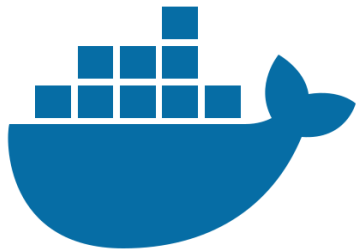
Slice pivoting [3]



Supply Chain Backdoor [4]

Features and flexibility at the cost of an increased attacking surface

Broader attacking surface



VM/Docker escape [1]



Man in the Middle [2]



Fuzzing [2]



Slice pivoting [3]



Supply Chain Backdoor [4]

Control Plane Network Messages

Features and flexibility at the cost of an increased attacking surface

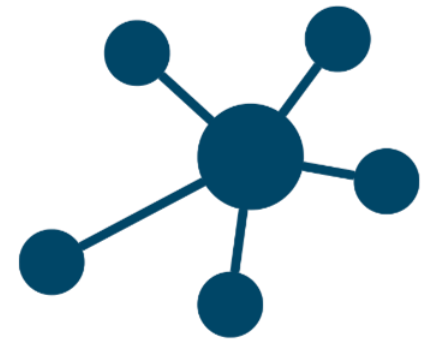
Anomaly Dimensions



Semantic

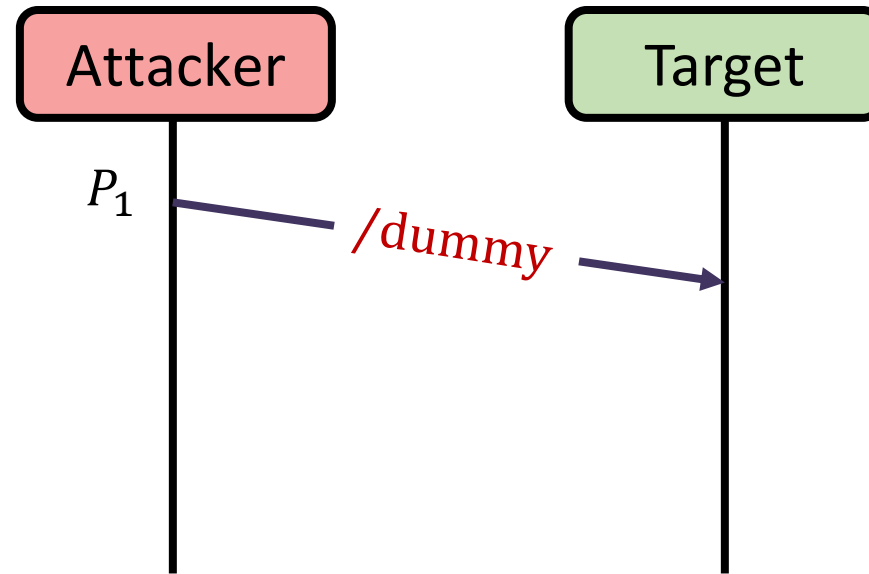


Sequence



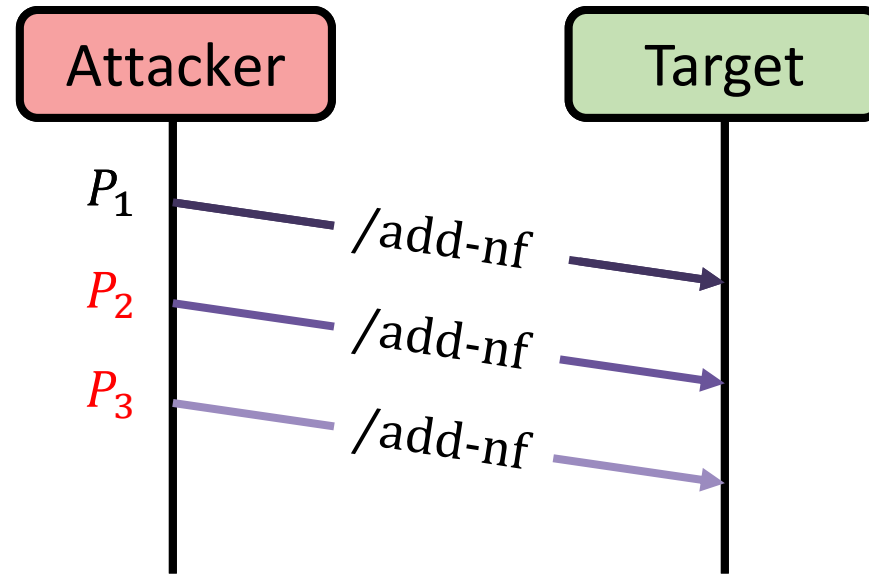
Topology

Anomaly 1 : Semantic



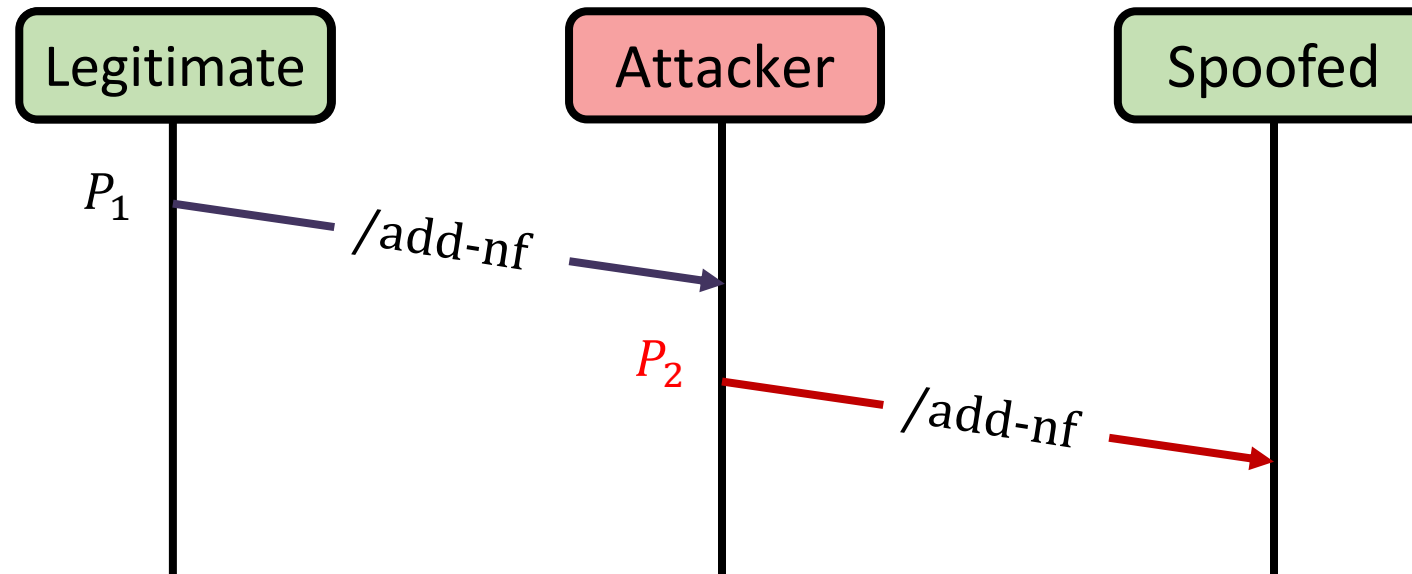
Example : API Fuzzing [2]

Anomaly 2 : Sequential



Example : Session Flooding [5]

Anomaly 3 : Topologic



Example : *Man in the Middle* [2]

5G Anomaly Detection SoTA

What are they missing ?

State of the art for 5G anomaly detection

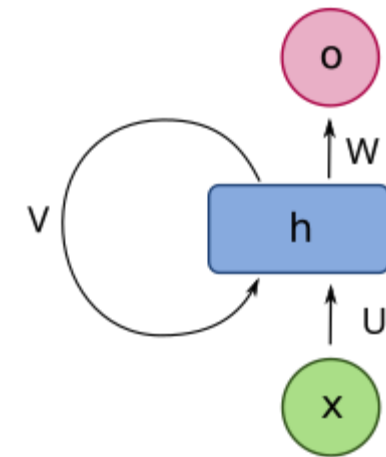
Sequences of Interactions

$F_{expected} = \{gNB \rightarrow AMF, AMF \rightarrow AUSF, AUSF \rightarrow AMF, AMF \rightarrow AUSF, AUSF \rightarrow AMF, AUSF \rightarrow UDM, UDM \rightarrow AUSF, UDM \rightarrow UDR, UDR \rightarrow UDM, \dots\}$

$F_{actual} = \{gNB \rightarrow AMF, AMF \rightarrow AUSF, AUSF \rightarrow AMF, AMF \rightarrow AUSF, AUSF \rightarrow AMF, SMF \rightarrow AMF, SMF \rightarrow AMF, SMF \rightarrow AMF, AUSF \rightarrow UDM, \dots\}$

- $S_1 = [gNB \rightarrow AMF, AMF \rightarrow AUSF, AUSF \rightarrow AMF, AMF \rightarrow AUSF, AUSF \rightarrow AMF] \rightarrow E_{next-predict} \text{ match } E_{next-expected} = [AUSF \rightarrow UDM]$
- $S_2 = [AMF \rightarrow AUSF, AUSF \rightarrow AMF, AMF \rightarrow AUSF, AUSF \rightarrow AMF, SMF \rightarrow AMF] \rightarrow E_{next-predict} \text{ mismatch } E_{next-expected} = [UDM \rightarrow AUSF]$
- $S_3 = [AUSF \rightarrow AMF, AMF \rightarrow AUSF, AUSF \rightarrow AMF, SMF \rightarrow AMF, SMF \rightarrow AMF] \rightarrow E_{next-predict} \text{ mismatch } E_{next-expected} = [UDM \rightarrow UDR]$
- $S_4 = [AMF \rightarrow AUSF, AUSF \rightarrow AMF, SMF \rightarrow AMF, SMF \rightarrow AMF, SMF \rightarrow AMF] \rightarrow E_{next-predict} \text{ mismatch } E_{next-expected} = [UDR \rightarrow UDM]$

Recurrent Neural Network



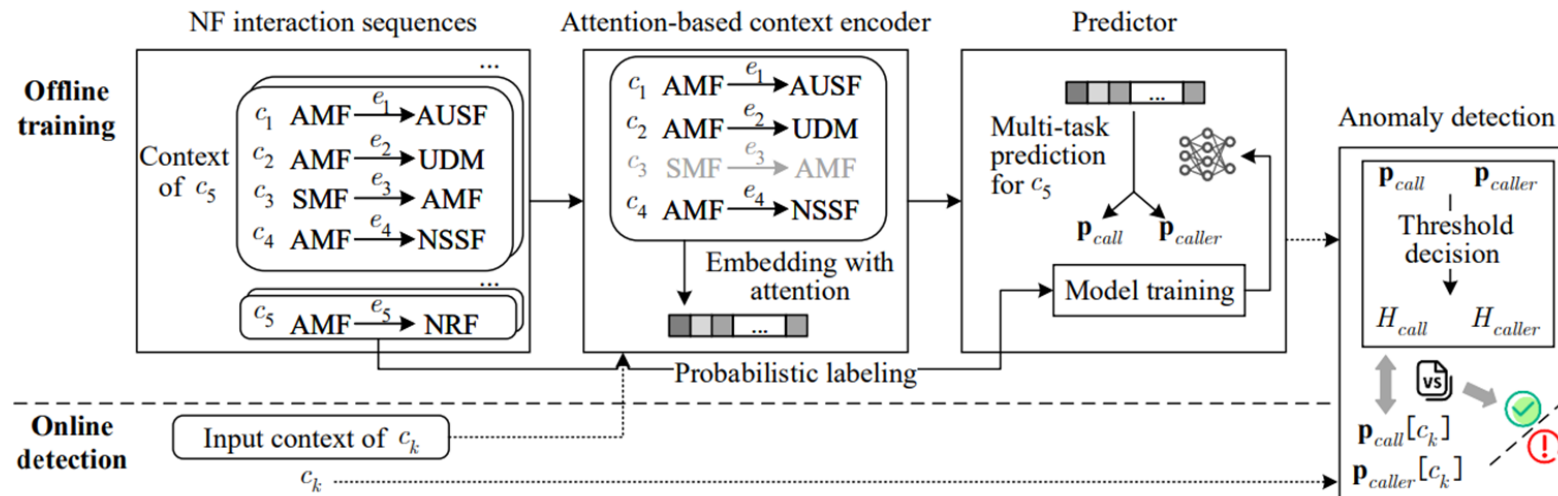
ADSeq-5GCN [6]

Semantic ✗ Sequential Topologic 😬

[6] Z. Tian, R. Patil, M. Gurusamy, et J. McCloud, « ADSeq-5GCN: Anomaly Detection from Network Traffic Sequences in 5G Core Network Control Plane », in *2023 IEEE 24th International Conference on High Performance Switching and Routing (HPSR)*, juin 2023, p. 75-82. doi: [10.1109/HPSR57248.2023.10147931](https://doi.org/10.1109/HPSR57248.2023.10147931).

State of the art for 5G anomaly detection

Sequences of Interactions (+ Endpoint)



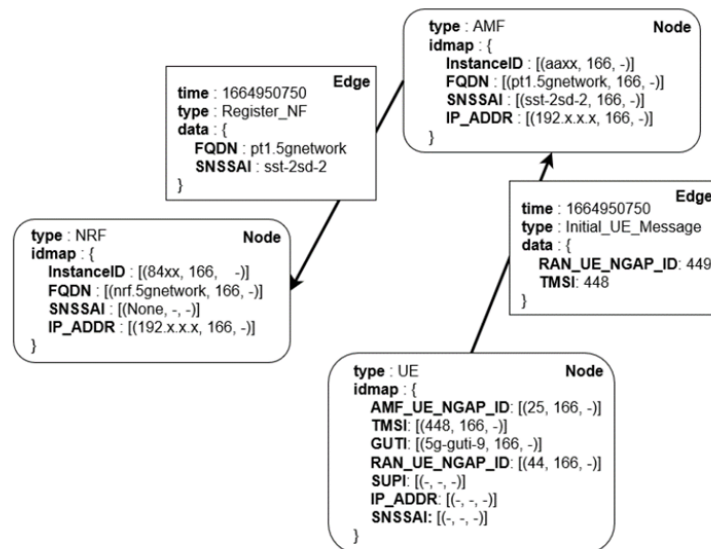
5GCGuard [7]

Semantic ✗ Sequential ✓ Topologic 😞

[7] Y. Tan, J. Liu, Y. Li, et J. Wang, « Deep Learning Based Proactive Anomaly Detection for 5G Core Control Plane Network Function Interactions », *IEEE Transactions on Cognitive Communications and Networking*, p. 1-1, 2025, doi: [10.1109/TCCN.2025.3539660](https://doi.org/10.1109/TCCN.2025.3539660).

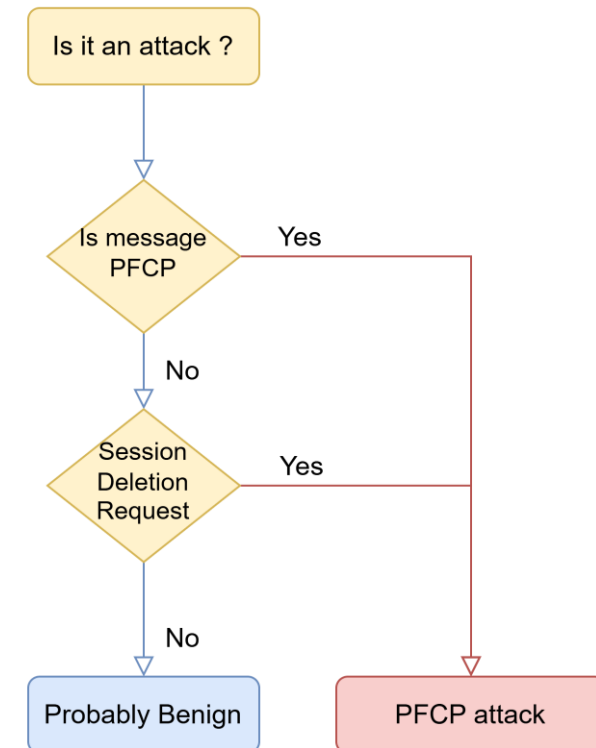
State of the art for 5G anomaly detection

Provenance Graph



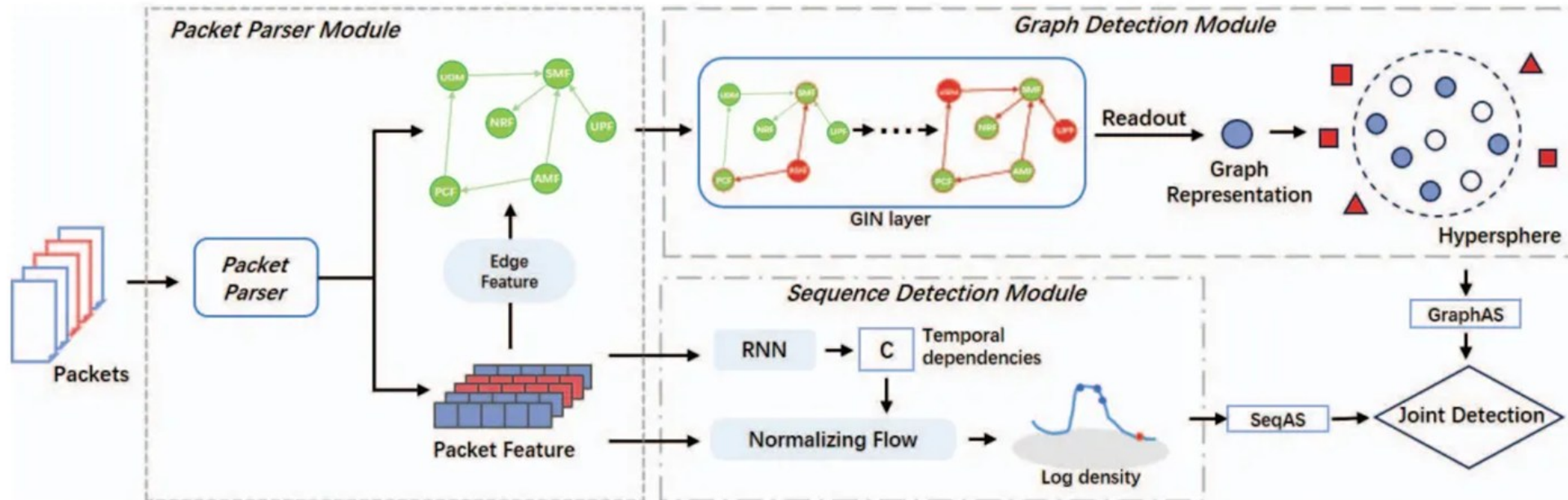
Prov5G [8]

Semantic 🤔 Sequential ✗ Topologic ✓



[8] H. S. Pacherkar et G. Yan, « PROV5GC: Hardening 5G Core Network Security with Attack Detection and Attribution Based on Provenance Graphs », in *Proceedings of the 17th ACM Conference on Security and Privacy in Wireless and Mobile Networks*, in WiSec '24. New York, NY, USA: Association for Computing Machinery, mai 2024, p. 254-264. doi: [10.1145/3643833.3656129](https://doi.org/10.1145/3643833.3656129).

State of the art for 5G anomaly detection

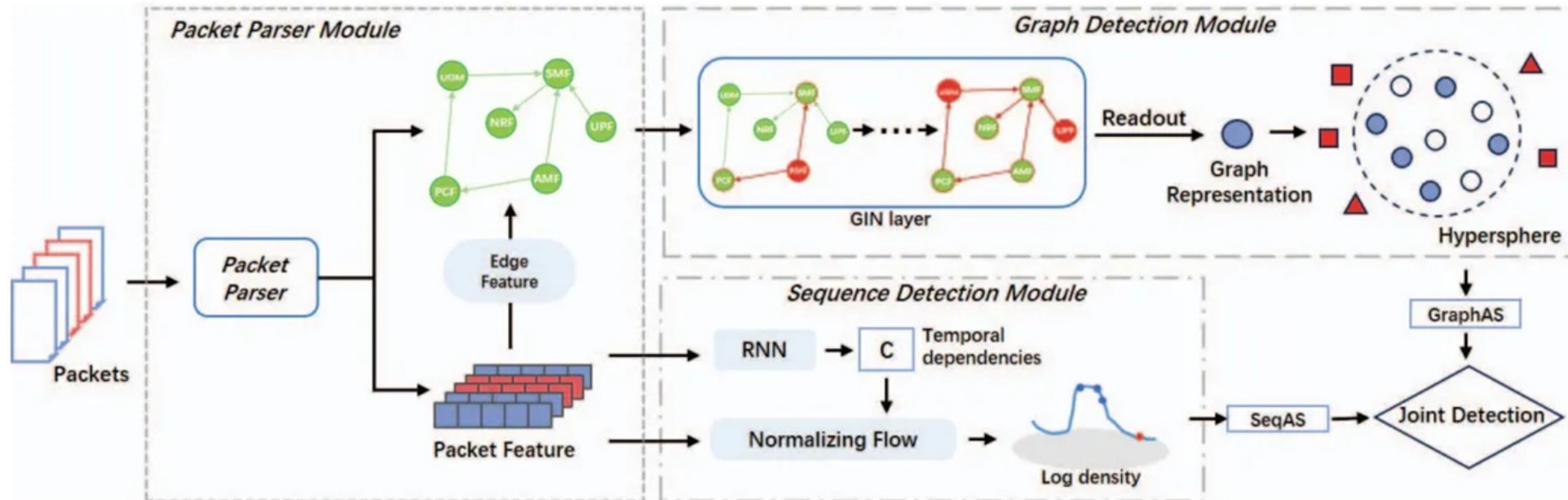


GSAD [9]

Semantic ☹ Sequential ☹ Topologic ✓

[9] M. Wang *et al.*, « Unsupervised Graph-Sequence Anomaly Detection for 5G Core Network Control Plane Traffic », in *2023 IEEE 29th International Conference on Parallel and Distributed Systems (ICPADS)*, déc. 2023, p. 1645-1652. doi: [10.1109/ICPADS60453.2023.00230](https://doi.org/10.1109/ICPADS60453.2023.00230).

State of the art for 5G anomaly detection



GSAD [9]

Semantic ☹ Sequential ☹ Topologic ✓

[9] M. Wang *et al.*, « Unsupervised Graph-Sequence Anomaly Detection for 5G Core Network Control Plane Traffic », in *2023 IEEE 29th International Conference on Parallel and Distributed Systems (ICPADS)*, déc. 2023, p. 1645-1652. doi: [10.1109/ICPADS60453.2023.00230](https://doi.org/10.1109/ICPADS60453.2023.00230).

Graph Formalization

How do we represent the network messages

Graph formalization of network traffic

```

4175 50.498176 localhost NRF HTTP2 639 HEADERS[5]: GET /nnrf-disc/v1/nf-instances?requester-nf-type=SMF&target-nf-instance-id=bb87e12b-e6fa-4
4180 50.501378 NRF localhost HTTP2 89 HEADERS[5]: 200 OK
4181 50.501455 NRF localhost HTTP2/JSON 2079 DATA[5], JSON (application/json)
  
```

```

> Frame 4181: 2079 bytes on wire (16632 bits), 2079 bytes captured (16632 bits)
> Linux cooked capture v2
> Internet Protocol Version 4, Src: NRF (127.0.0.10), Dst: localhost (127.0.0.1)
> Transmission Control Protocol, Src Port: 80, Dst Port: 34738, Seq: 768, Ack: 875, Len: 200
  
```

```

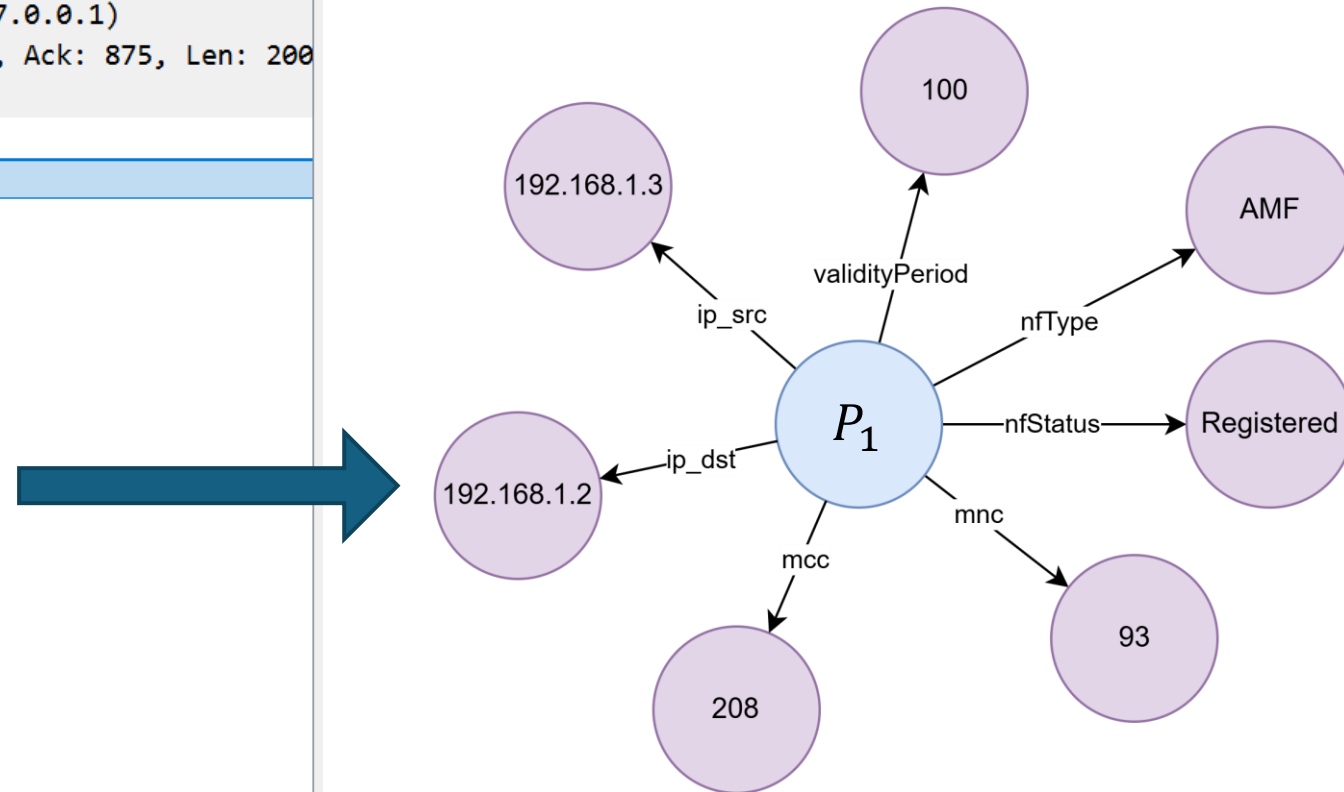
  > Stream: DATA, Stream ID: 5, Length 1998
  > JavaScript Object Notation: application/json
  
```

```

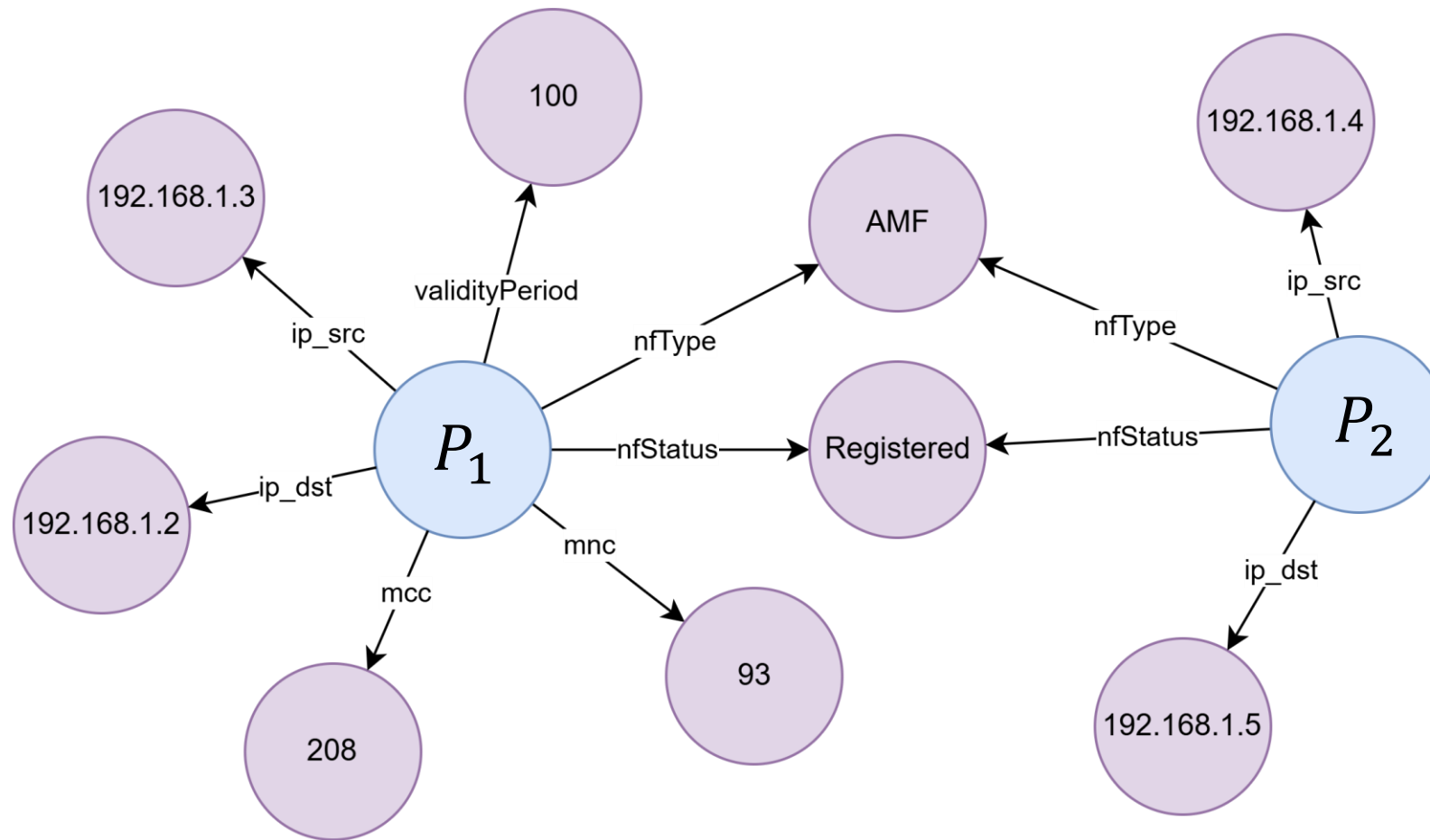
  > Object
    > Member: validityPeriod
    > Member: nfInstances
      > Array
        > Object
          > Member: nfInstanceId
          > Member: nfType
          > Member: nfStatus
          > Member: plmnList
          > Member: sNssais
          > Member: ipv4Addresses
          > Member: amfInfo
          > Member: customInfo
          > Member: nfServices
          > Member: defaultNotificationSubscriptions
  
```

Key: nfInstances

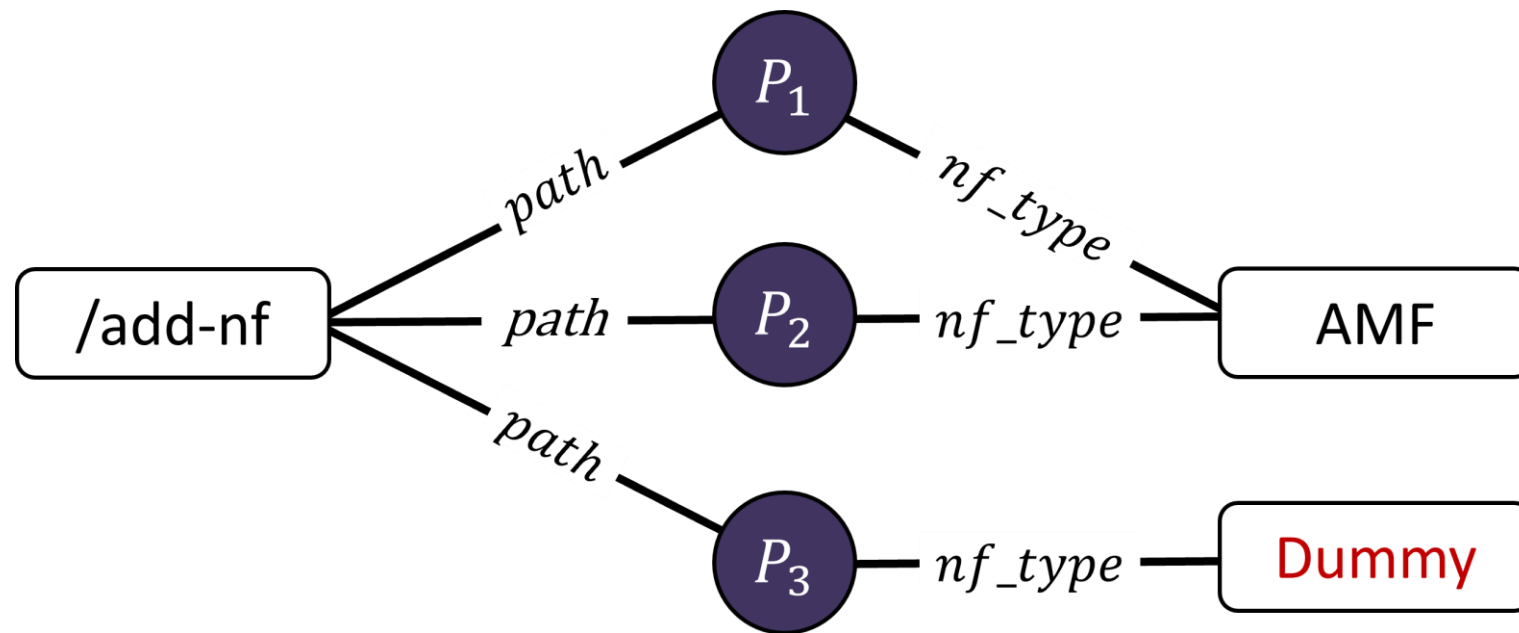
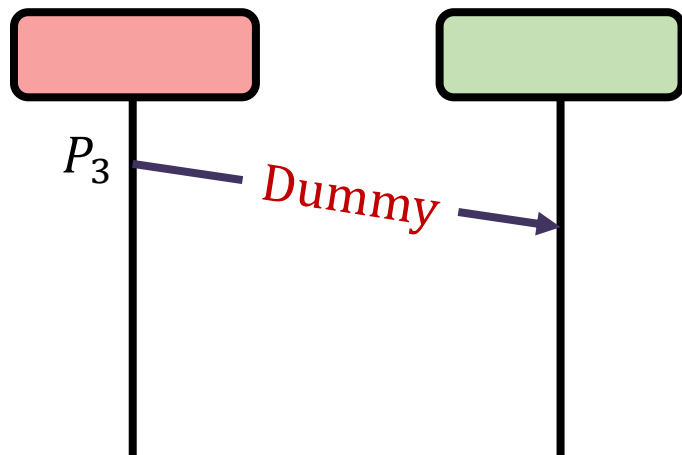
[Path: /nfInstances]



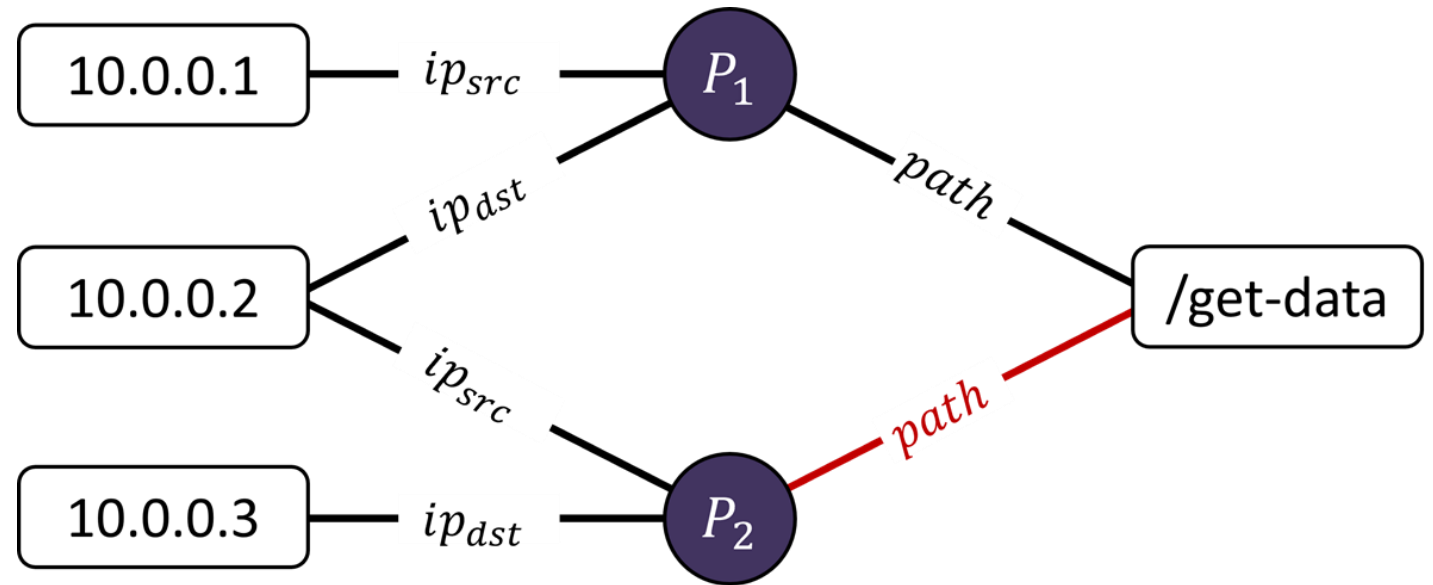
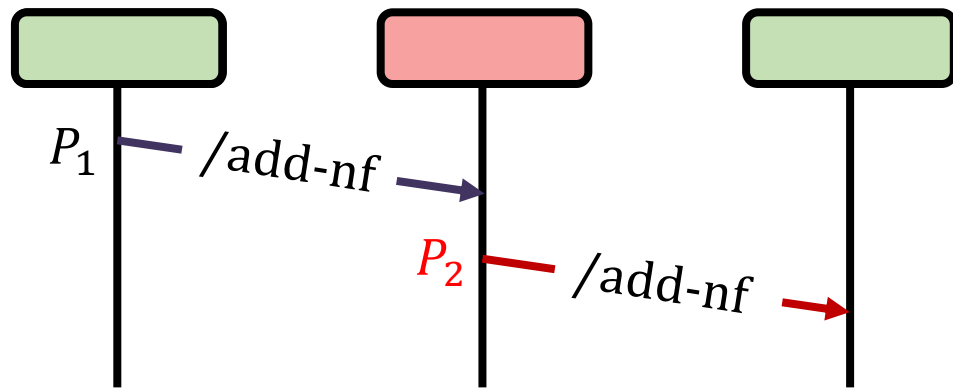
Graph formalization of network traffic



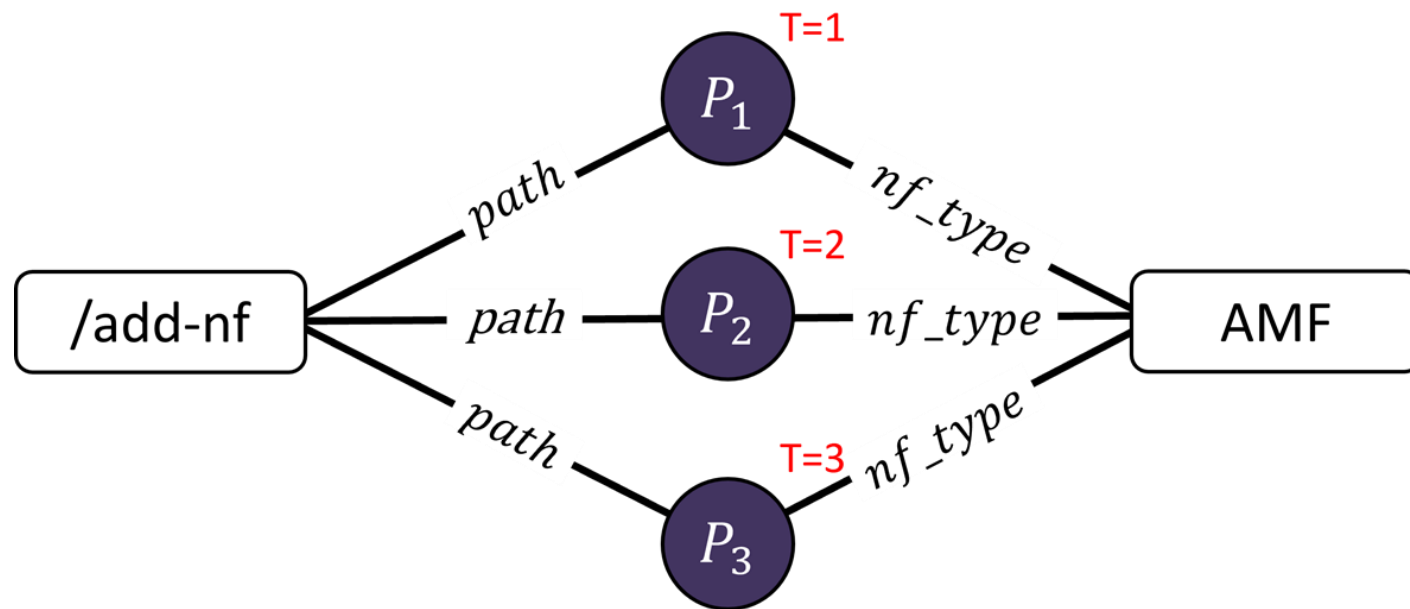
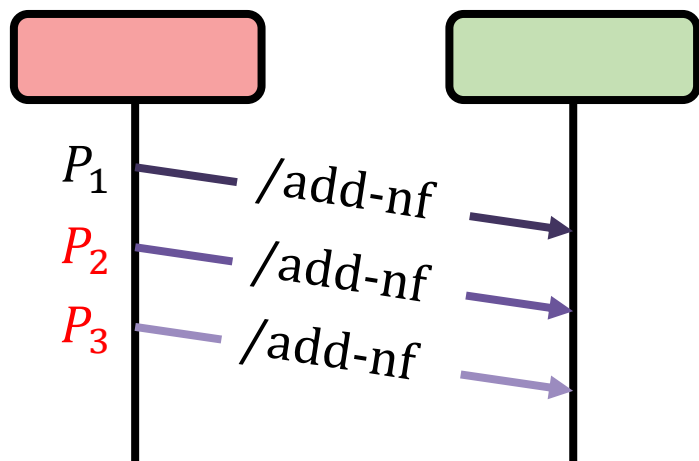
Anomaly 1 : Semantic



Anomaly 2 : Topologic



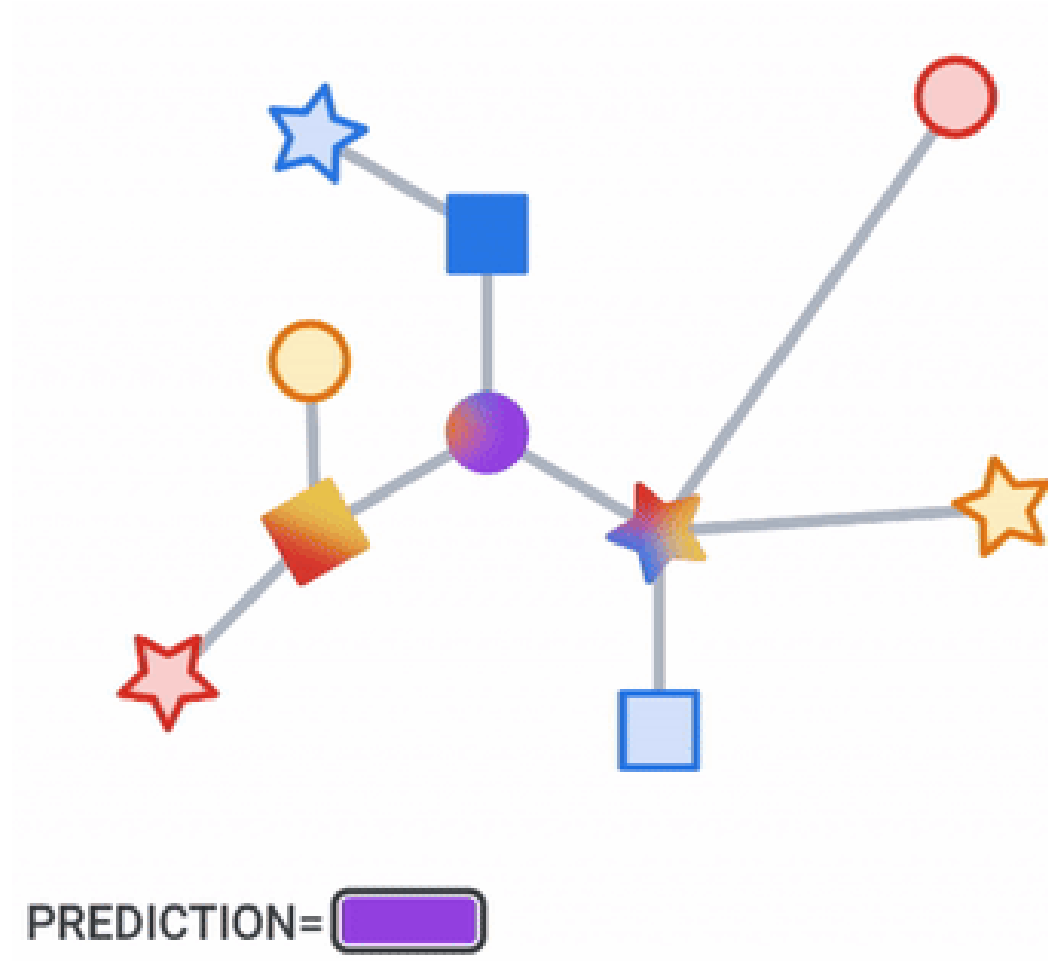
Anomaly 3 : Sequential



Graph Neural Network

How does it work and how to add the time aspect

Simple explanation of GNN operation



State of the art for GNN

Recent Domain



First paper [10] - 2008

Formalization [11] - 2017

[10] F. Scarselli, M. Gori, A. C. Tsoi, M. Hagenbuchner, et G. Monfardini, « The Graph Neural Network Model », *IEEE Transactions on Neural Networks*, vol. 20, n° 1, p. 61-80, janv. 2009, doi: [10.1109/TNN.2008.2005605](https://doi.org/10.1109/TNN.2008.2005605).

[11] J. Gilmer, S. S. Schoenholz, P. F. Riley, O. Vinyals, et G. E. Dahl, « Neural Message Passing for Quantum Chemistry », 12 juin 2017, arXiv:1704.01212. doi: [10.48550/arXiv.1704.01212](https://doi.org/10.48550/arXiv.1704.01212).

State of the art for GNN

Recent Domain



First paper [10] - 2008
Formalization [11] - 2017

Traditional GNN



Most GNN consider a single
Monolithic and Static graph

[10] F. Scarselli, M. Gori, A. C. Tsoi, M. Hagenbuchner, et G. Monfardini, « The Graph Neural Network Model », *IEEE Transactions on Neural Networks*, vol. 20, n° 1, p. 61-80, janv. 2009, doi: [10.1109/TNN.2008.2005605](https://doi.org/10.1109/TNN.2008.2005605).

[11] J. Gilmer, S. S. Schoenholz, P. F. Riley, O. Vinyals, et G. E. Dahl, « Neural Message Passing for Quantum Chemistry », 12 juin 2017, arXiv:1704.01212. doi: [10.48550/arXiv.1704.01212](https://doi.org/10.48550/arXiv.1704.01212).

State of the art for GNN

Recent Domain



First paper [10] - 2008
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Traditional GNN



Most GNN consider a single
Monolithic and Static graph

Dynamic GNN



Specific GNN called
Dynamic Graph Neural Network
This domain is even more recent [12]

Dynamic GNN

Dynamic **Graph Neural Network**
(DGNN)



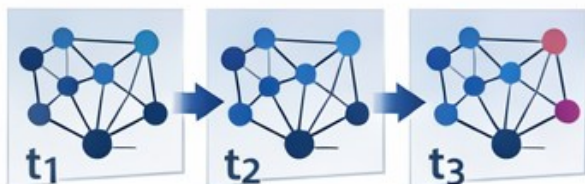
Dynamic GNN



Dynamic Graph Neural Network (DGNN)



Discrete Time Dynamic Graph (DTDG)



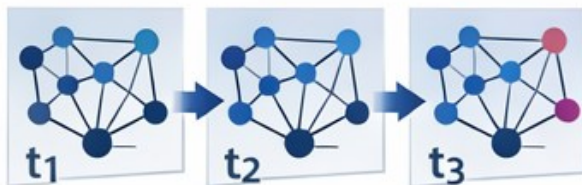
Graph snapshots at different time intervals
Each contain the entire graph state
Straightforward + Long time dependencies

Dynamic GNN

Dynamic Graph Neural Network (DGNN)



Discrete Time Dynamic Graph (DTDG)



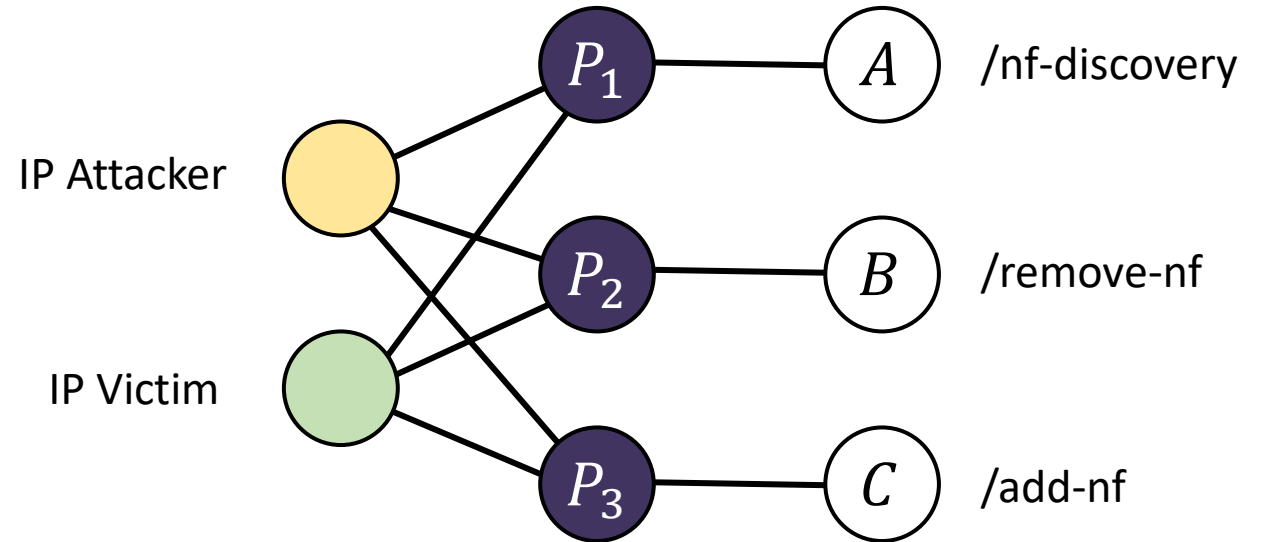
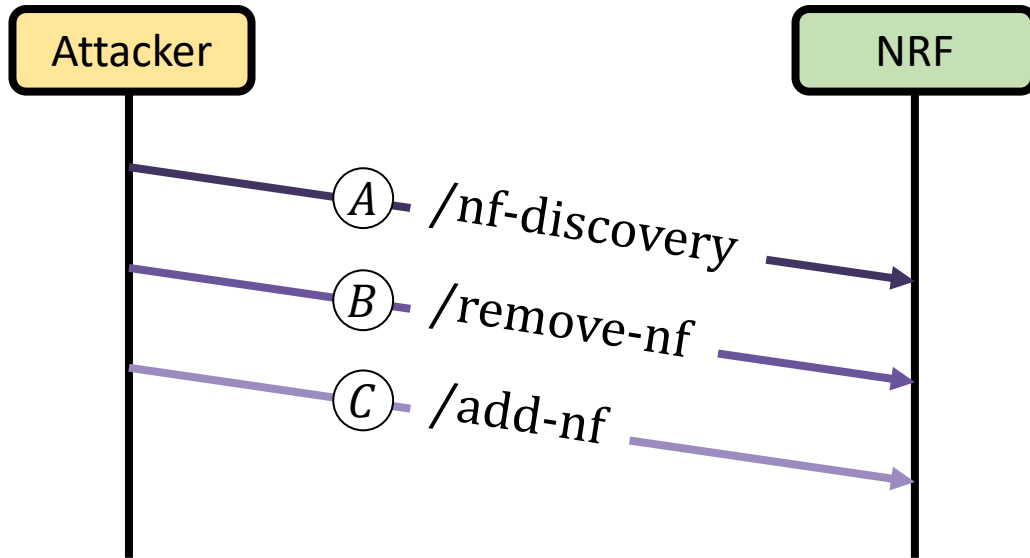
Graph snapshots at different time intervals
Each contain the entire graph state
Straightforward + Long time dependencies

Continuous Time Dynamic Graph (CTDG)

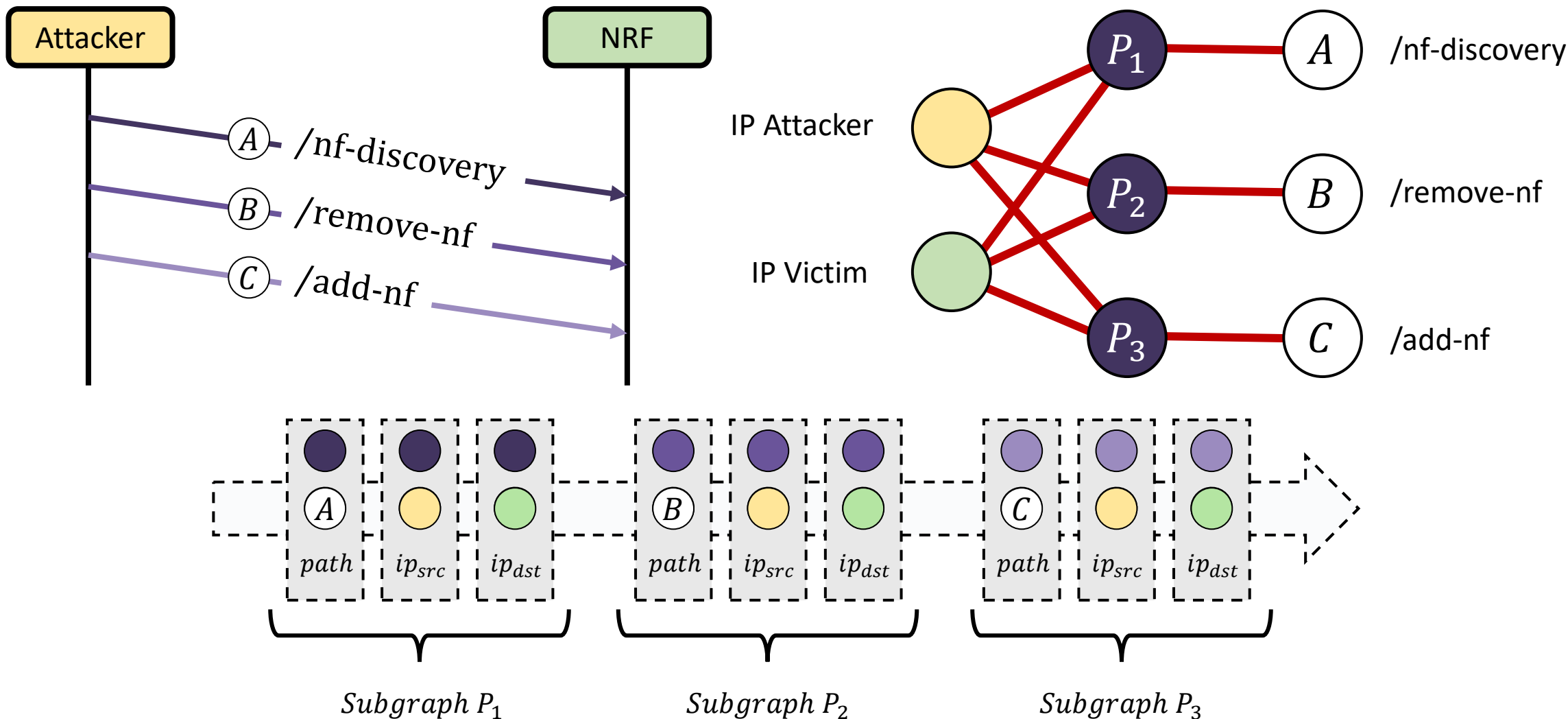
	t_1	t_i	t_n	t_{n+j}
Source	u	u	u	u'
Destination	v_1	v_i	v_n	v_i
Feature	x_1	x_i	x_n	x'_j
Benign	✓	✓	✓	✗

Event sequences (add, supp, modif..)
Represent the graph evolution at each step
No information loss + fine-grained

Example of CTDG transformation



Example of CTDG transformation



Model and Learning Process

How does the machine learn

Deeper explanation of GNNs

u and *v* initialized as null vector

Messages

Source Feature

u

Destination Feature

v

Time

Δt

Edge Feature

x

one hot encoding of edge features (Ex : ip_src, path, ...)

$$m(u) = \text{concat}(u, v, t, x)$$

Deeper explanation of GNNs

u and *v* initialized as null vector

Messages

Source Feature

u

Destination Feature

v

Time

Δt

Edge Feature

x

one hot encoding of edge features (Ex : ip_src, path, ...)

$$m(u) = \text{concat}(u, v, t, x)$$

Deeper explanation of GNNs

u and v initialized as null vector

Messages

Source Feature

u

Destination Feature

v

Time

Δt

Edge Feature

x

Memory

$s(u)$

If a node have already been seen
We take its previously saved value

Deeper explanation of GNNs

Messages

Source Feature

u

Destination Feature

v

Time

Δt

Edge Feature

x



Neighbors

$m_i(u)$

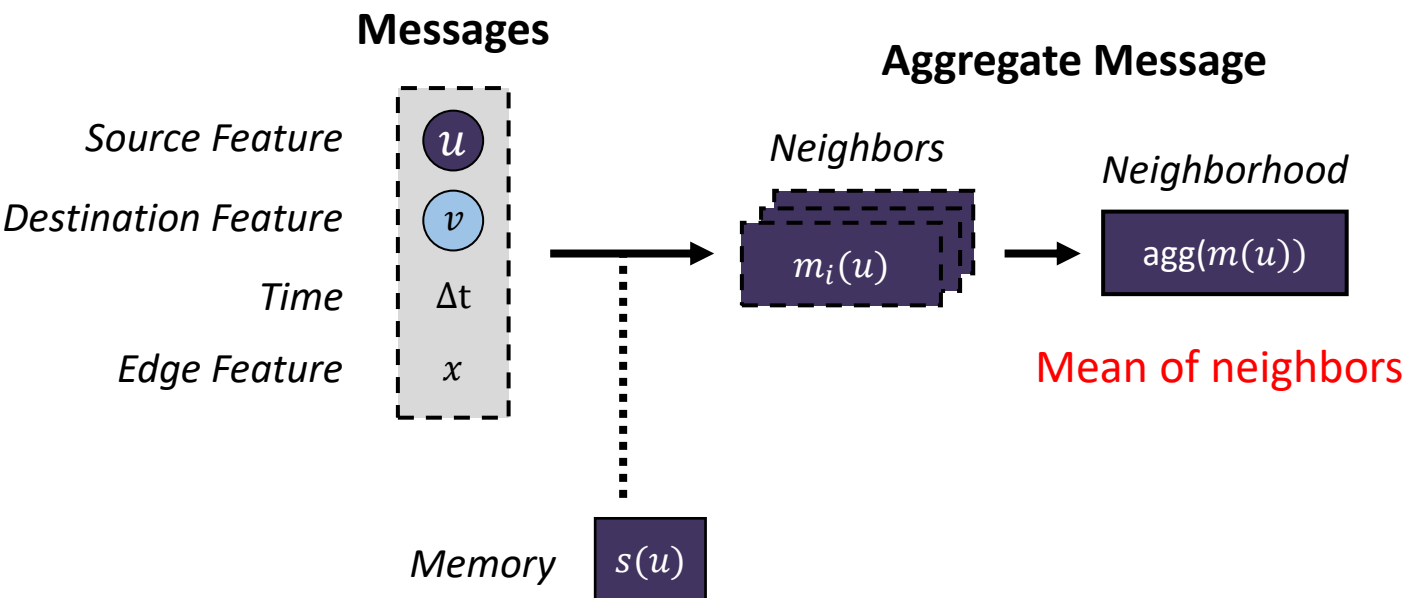
Every events related to u

Memory

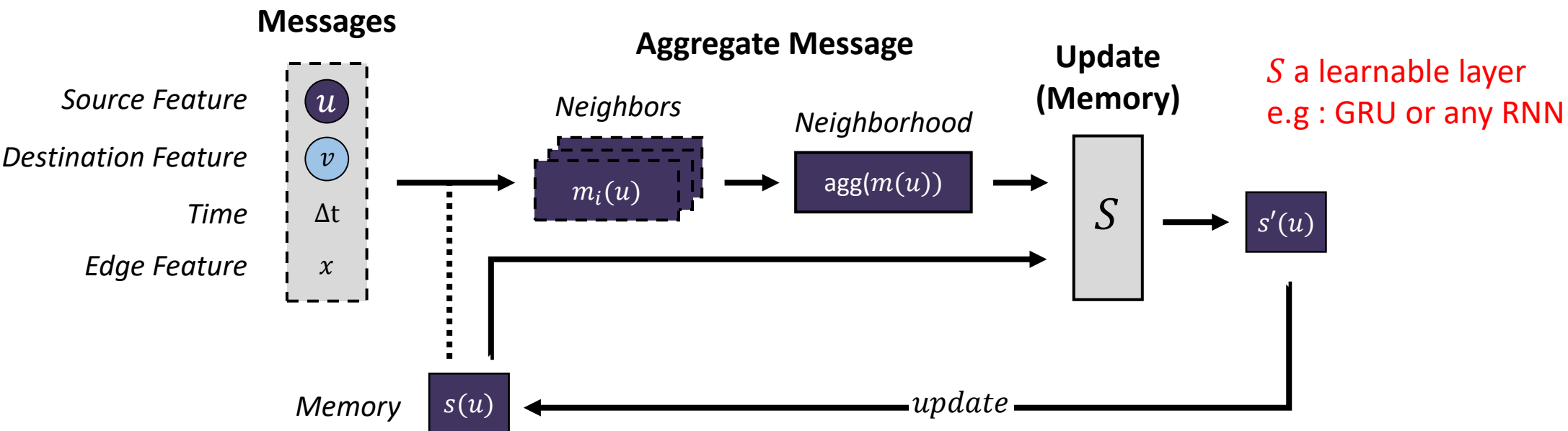
$s(u)$



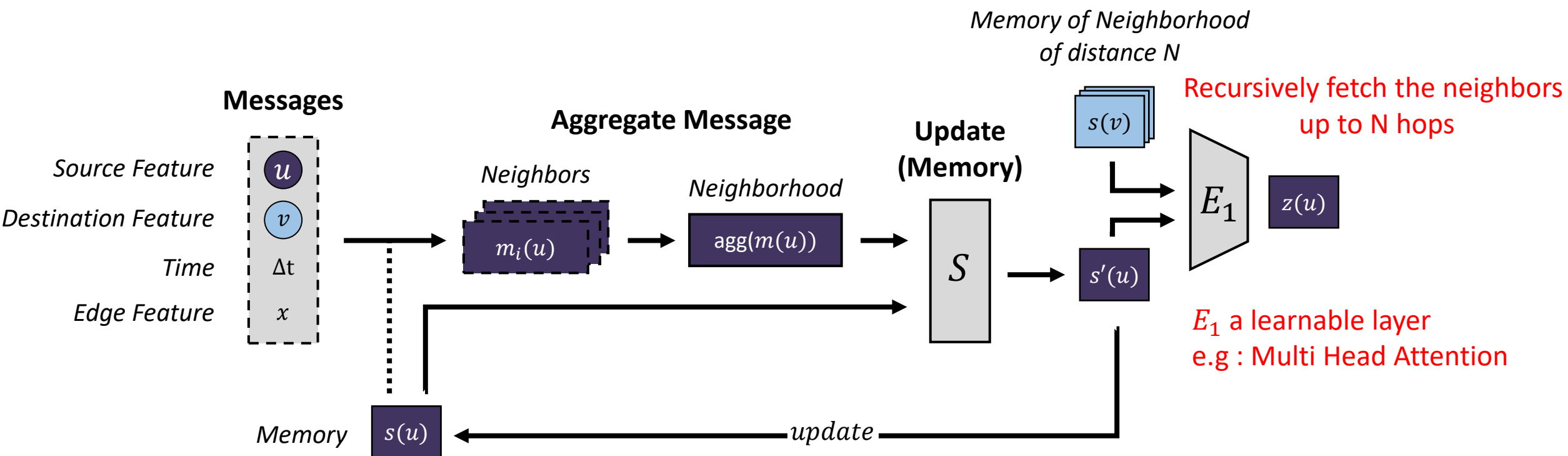
Deeper explanation of GNNs



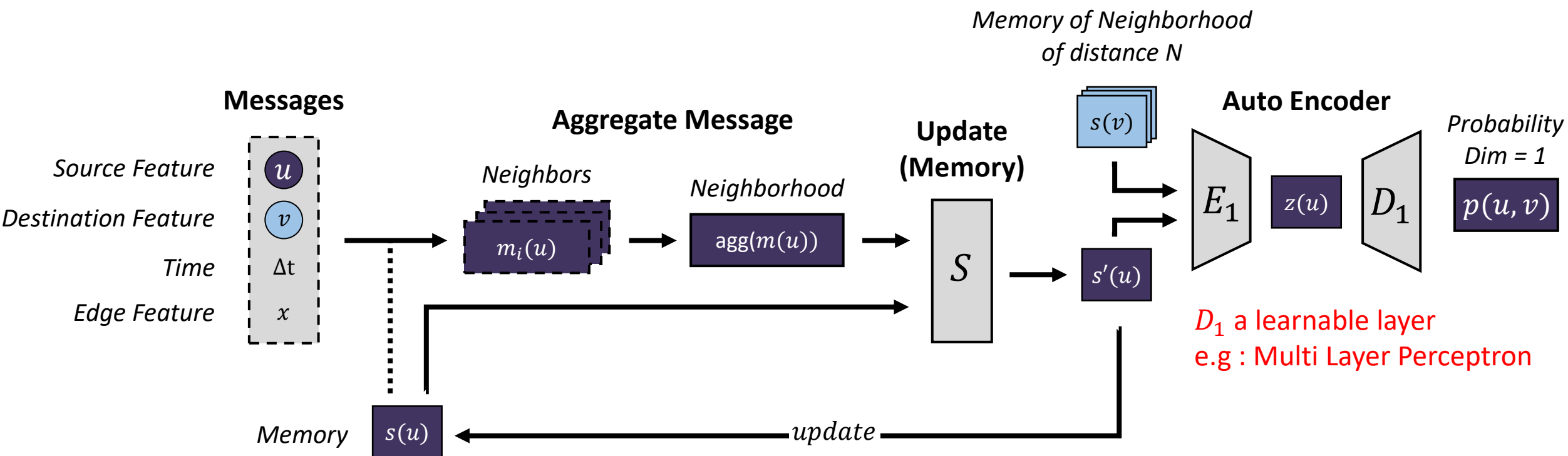
Deeper explanation of GNNs



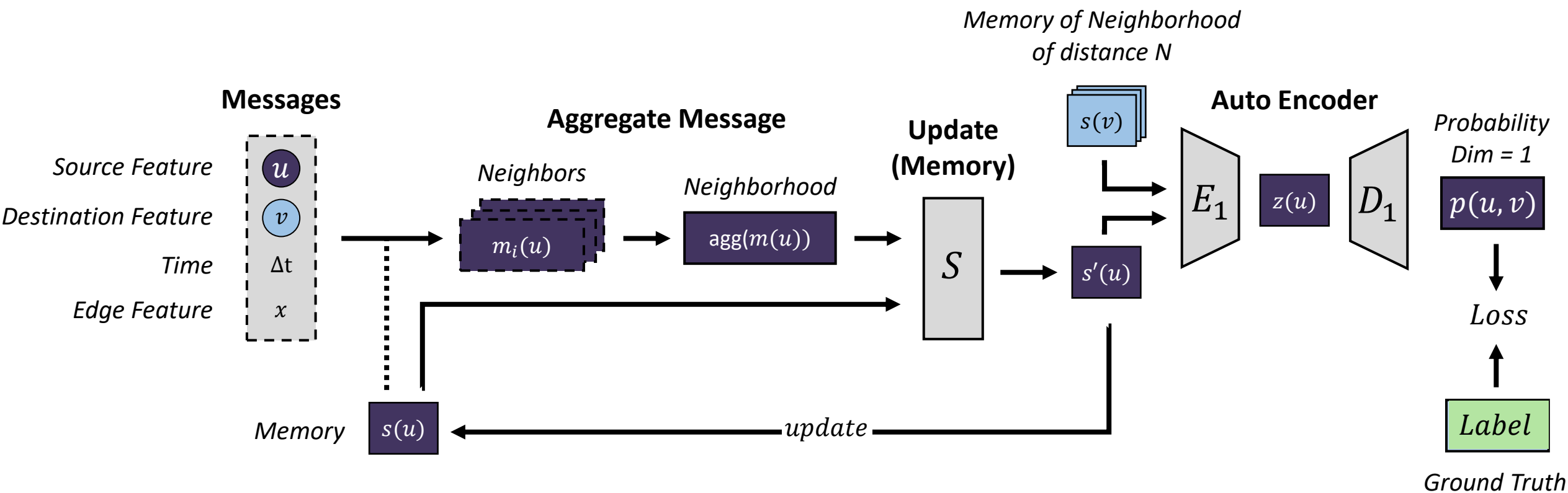
Deeper explanation of GNNs



Deeper explanation of GNNs



Deeper explanation of GNNs



Experimentation

Dataset content and process

Dataset State of the Art

Dataset	PCAP available	Code available	Benign procedures				
			(De)registration	Session management	State switching	NF management	UPF Forwarding
5GAD [13]	✓	✓					
PFCP IDD [14]	✓						
GSAD			✓				
AdSeq			✓	✓			
Prov5G			✓	✓	✓		
5GCguard		✓	✓	✓			
Our solution	✓	✓	✓	✓	✓	✓	✓

[13] C. Coldwell *et al.*, « Machine Learning 5G Attack Detection in Programmable Logic », in *2022 IEEE Globecom Workshops (GC Wkshps)*, déc. 2022, p. 1365-1370. doi: [10.1109/GCWkshps56602.2022.10008647](https://doi.org/10.1109/GCWkshps56602.2022.10008647).

[14] G. Amponis *et al.*, « 5G Core PFCP Intrusion Detection Dataset », in *2023 12th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, juin 2023, p. 1-4. doi: [10.1109/MOCAST57943.2023.10176693](https://doi.org/10.1109/MOCAST57943.2023.10176693).

Experiments with CTD5G Dataset

Benign			Attack		
Name	Procedure Count	Packet Count	Name	Procedure Count	Packet Count
Register UE	591	467,638	Fuzz	107	33,308
Restart Session	562	379,181	CN MiTM	123	22,587
User Traffic	317	159,228	SEID Fuzzing	116	23,858
Set UE Idle	288	67,124	Flood Establishment	113	23,949
Uplink Wake	137	55,599	Flood Deletion	98	20,446
Deregister UE	276	50,279	Applicative Scan	81	4,997
Downlink Wake	279	21,884	Modify Duplicate	119	345
Add NF	261	18,232	Modify Drop	100	292
Remove NF	253	16,336	Uplink Spoofing	102	102
			PFCP in GTP	101	101
Total	2,265	1,235,501	Total	1,060	129,985

Experiments with CTD5G Dataset

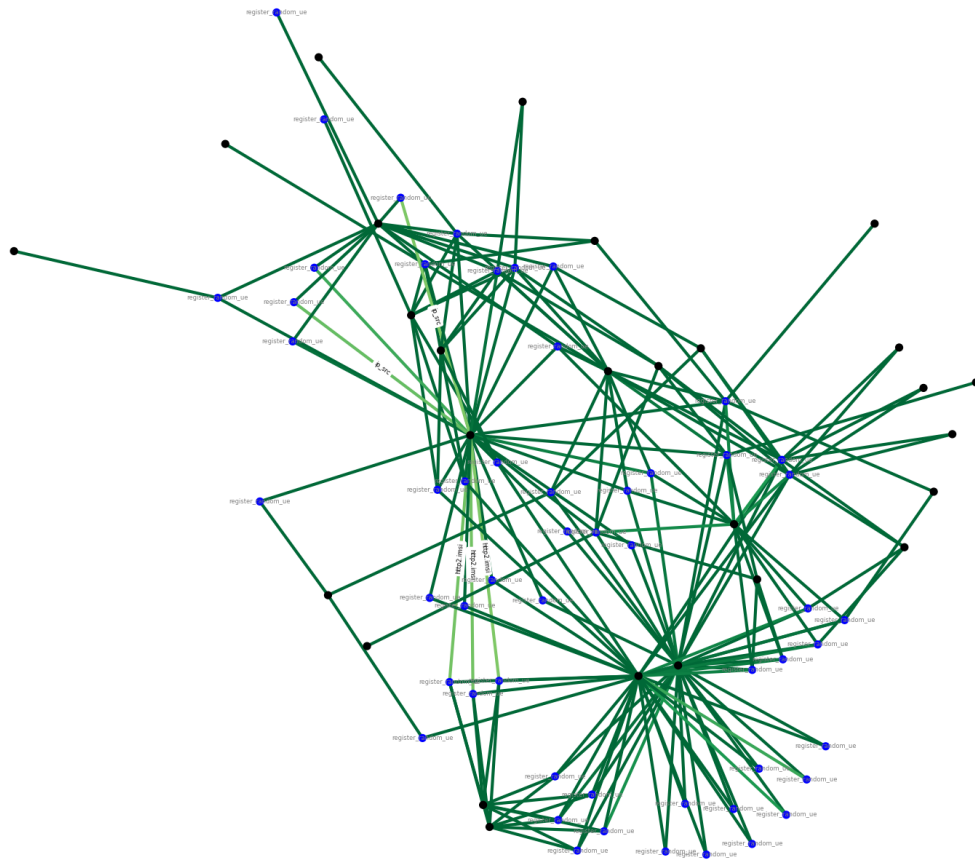
Attack name	Semantic	Sequential	Interaction
Applicative MiTM			✗
Applicative Scan		✗	✗
API Fuzzing	✗	✗	
Session Establishment Flood		✗	
Session Deletion Flood		✗	
SEID Fuzzing	✗	✗	
Session Modify Drop	✗	✗	
Session Modify Duplicate	✗	✗	
Uplink Spoofing	✗		✗
PFCP in GTP	✗		✗

Results : Metrics

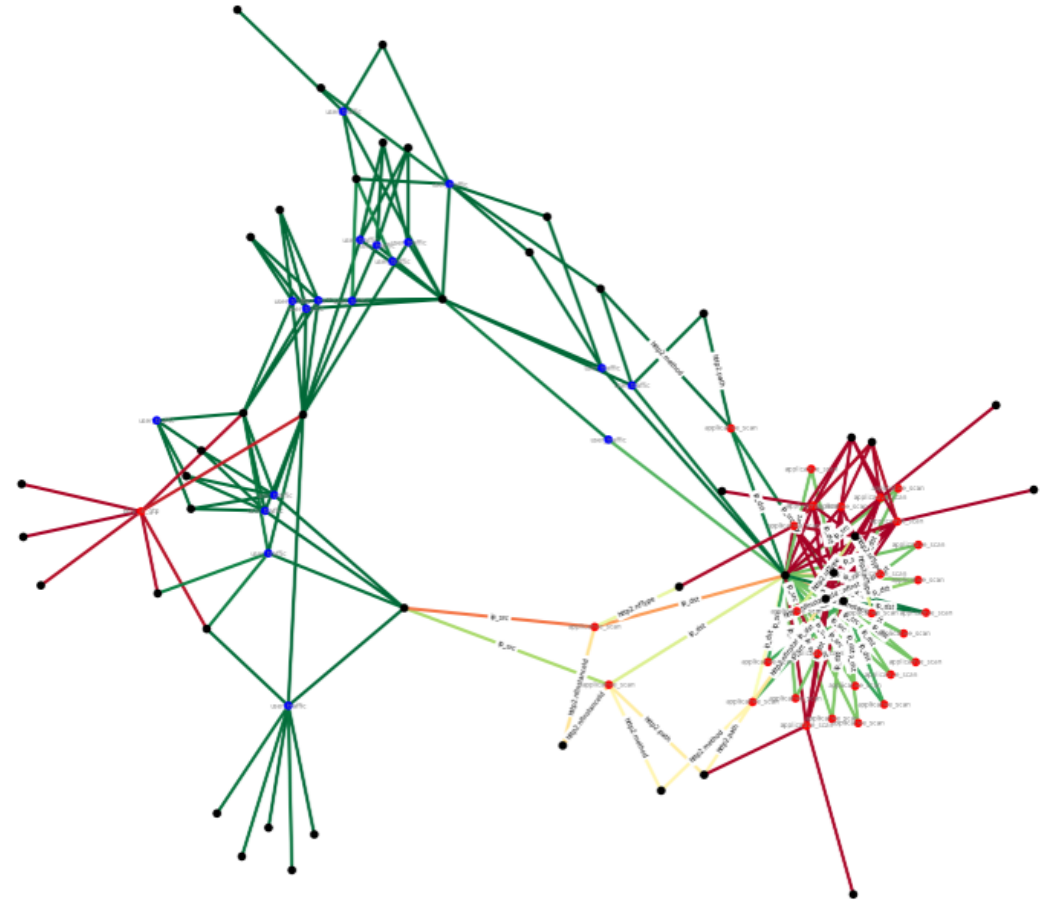
Metric	JODIE	DyRep	CAWN	DyGFormer	TCL	GraphMixer	TGN
Accuracy	0.7432	0.7581	0.7514	0.8386	0.8466	0.8361	<u>0.9497</u>
Precision	0.7226	0.8112	0.9611	0.9224	0.8916	0.9041	<u>0.9509</u>
Recall	0.1954	0.3568	0.1548	0.4879	0.5404	0.4906	<u>0.8727</u>
F1 Score	0.3077	0.4956	0.2666	0.6383	0.6729	0.6360	<u>0.9102</u>

<https://github.com/yule-buaa/dyglib>

Results : Explainability



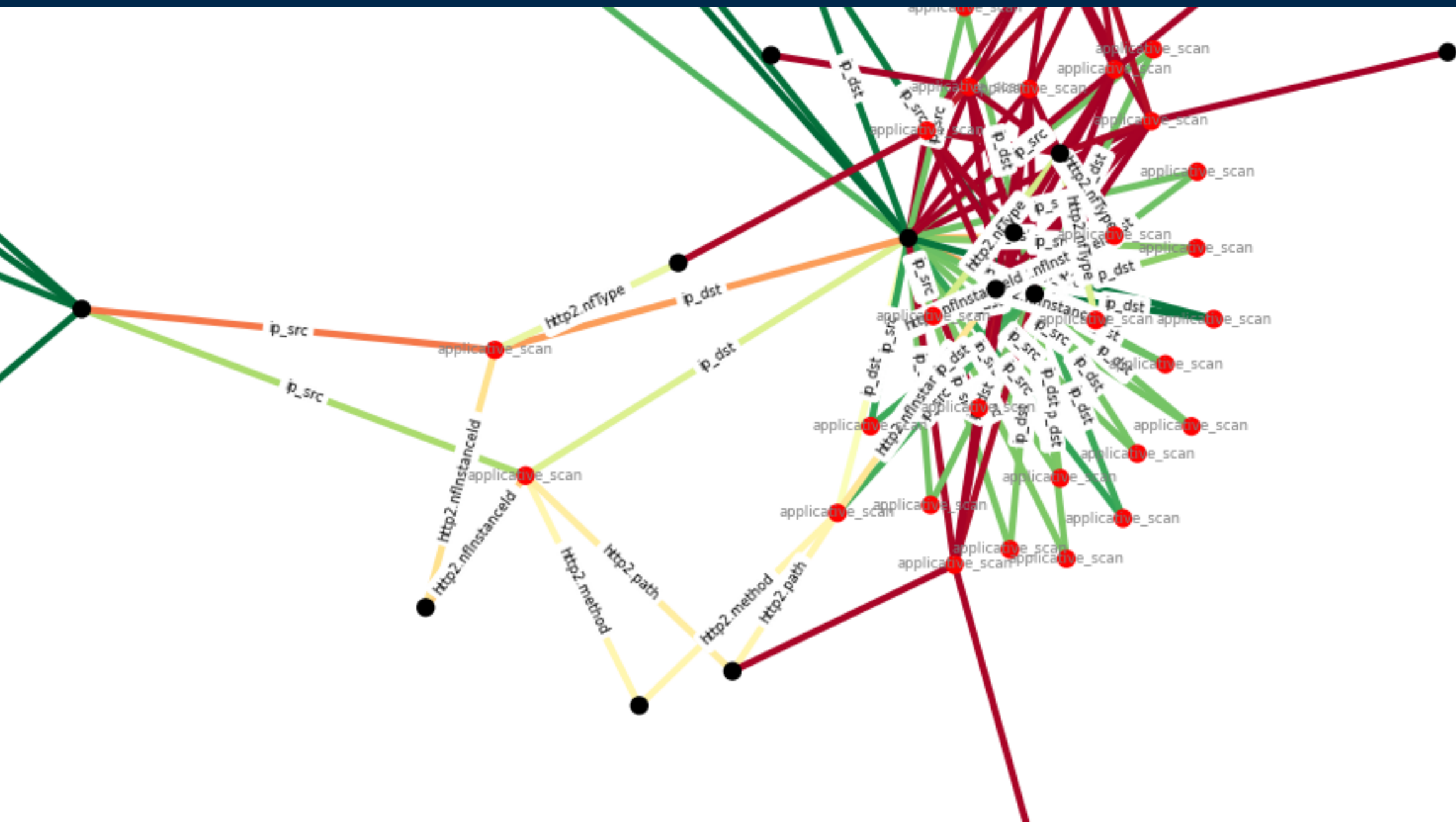
Benign (UE registration)



Attack (NF Scanning)

Thank you for your attention

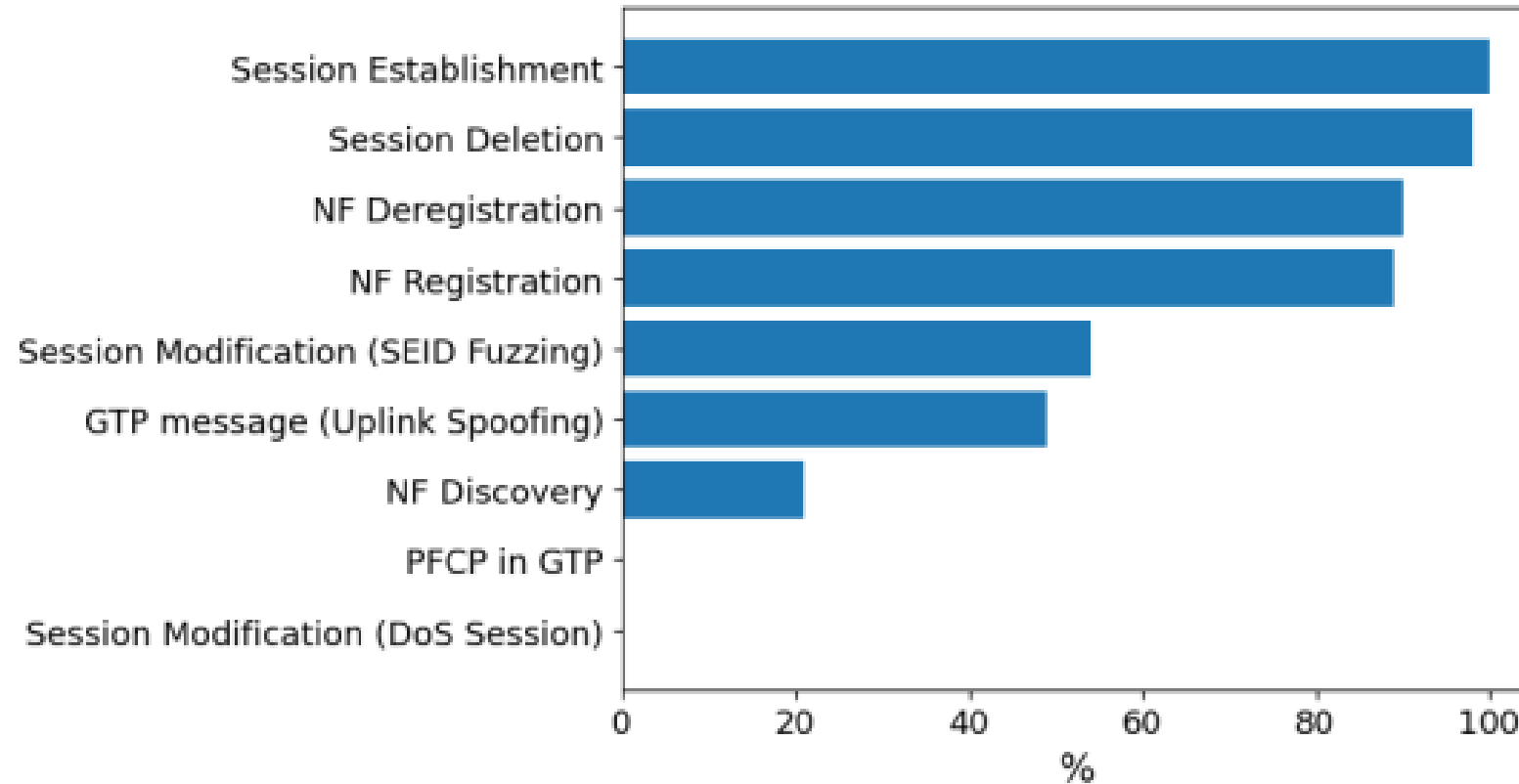
Do you have questions ?



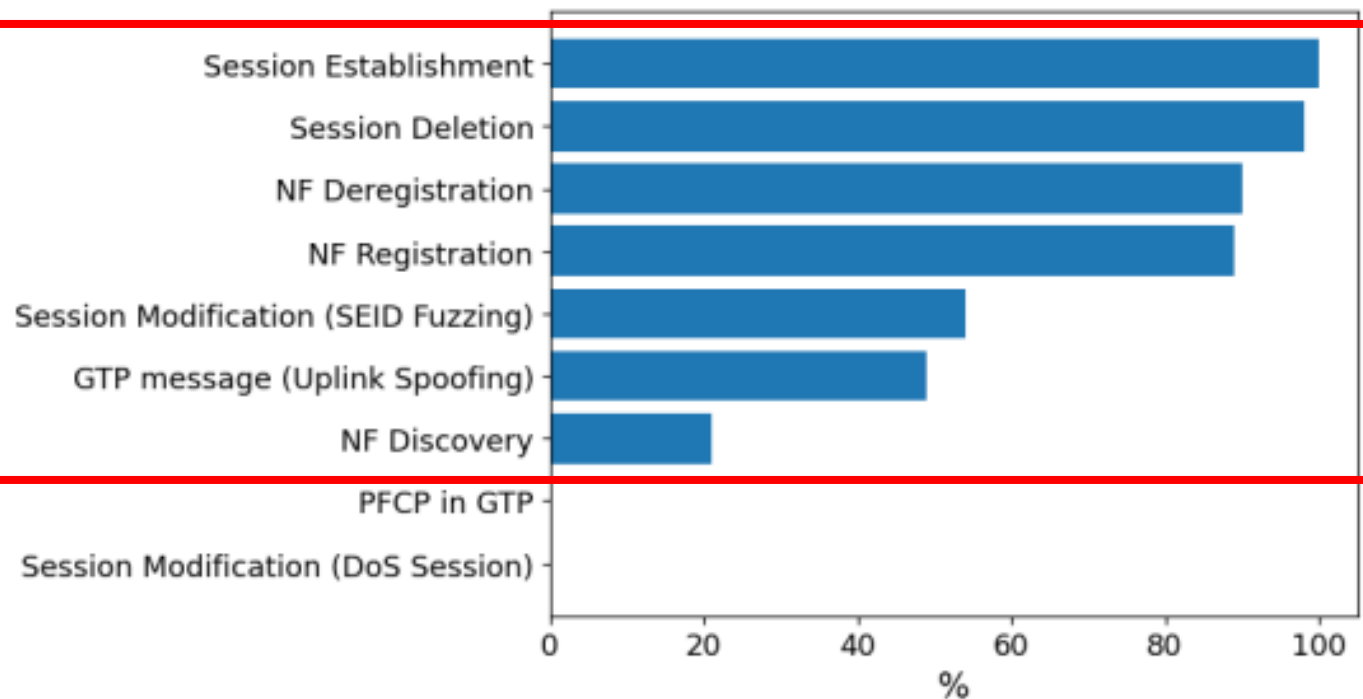
Property Evaluation

Characterizing each type of attacks

Analyzing semantic diversity

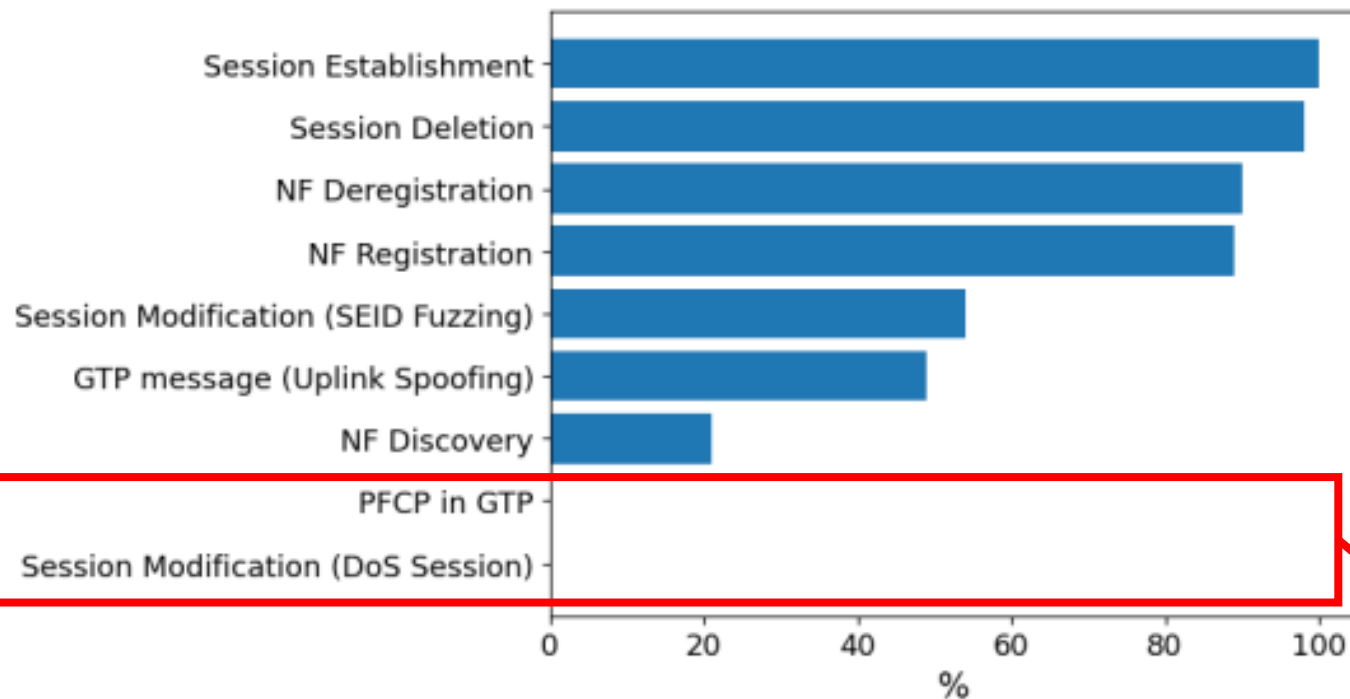


Analyzing semantic diversity



There exist at least **some** benign packets that are semantically identical to attack packets

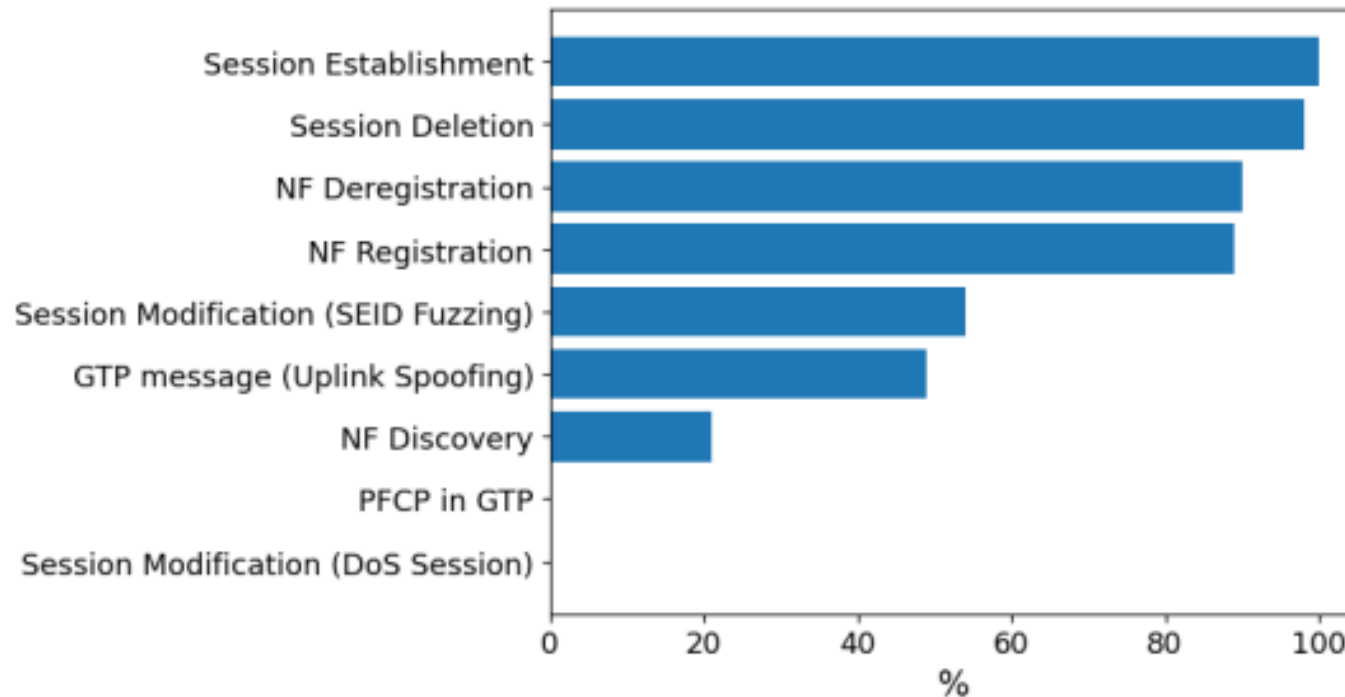
Analyzing semantic diversity



Malicious procedure	Comparable benign messages	Detection Type
Applicative NF scanning	NF Discovery	Repetition
API fuzzing	Any API call	Repetition / Semantic
Man-in-the-middle in the CN	NF Discovery and (De)registration	Interactions
Establishment flooding	Session establishment	Repetition
Deletion flooding	Session deletion	Repetition
Session DoS	Session modification	Repetition / Semantic
SEID fuzzing	Session modification	Repetition
PFCP-in-GTP	Any GTP message	Semantic
Uplink spoofing	Any GTP message	Interactions

There is no such message in benign traffic

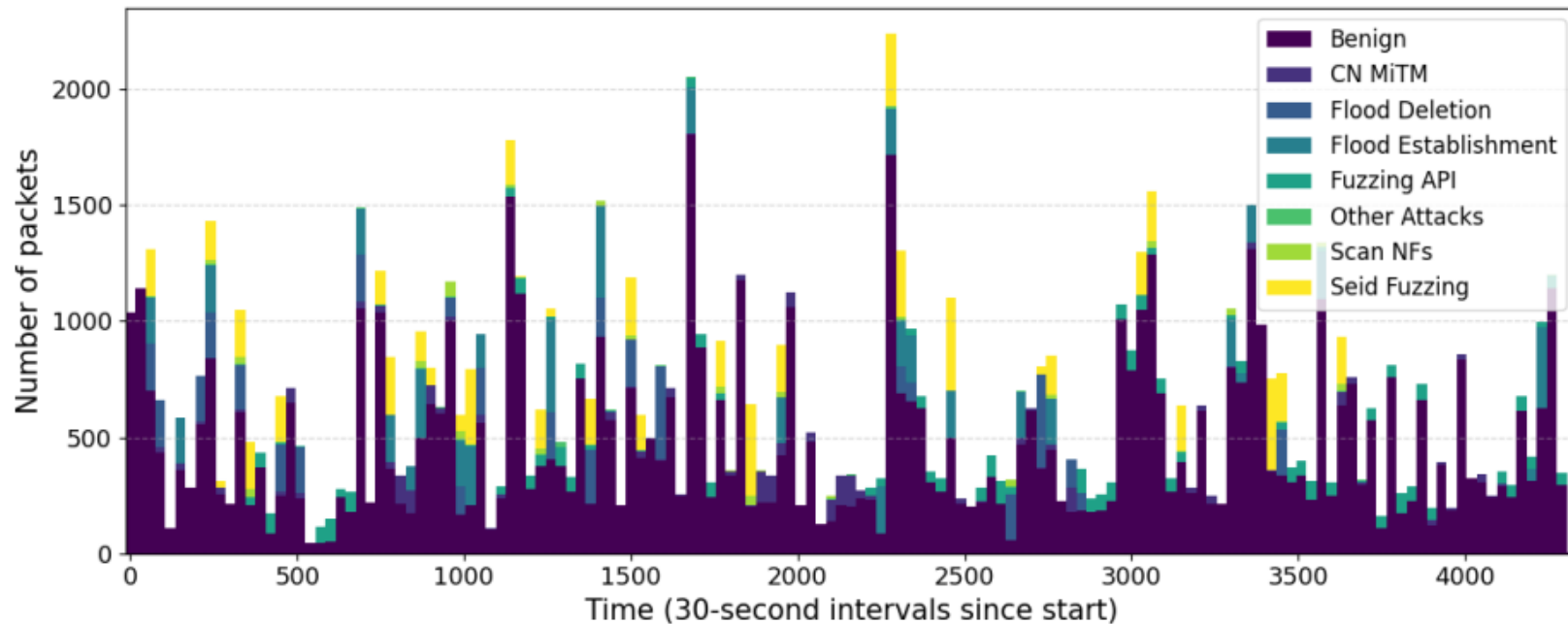
Analyzing semantic diversity



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PFCP-in-GTP	Any GTP message	Semantic
Uplink spoofing	Any GTP message	Interactions

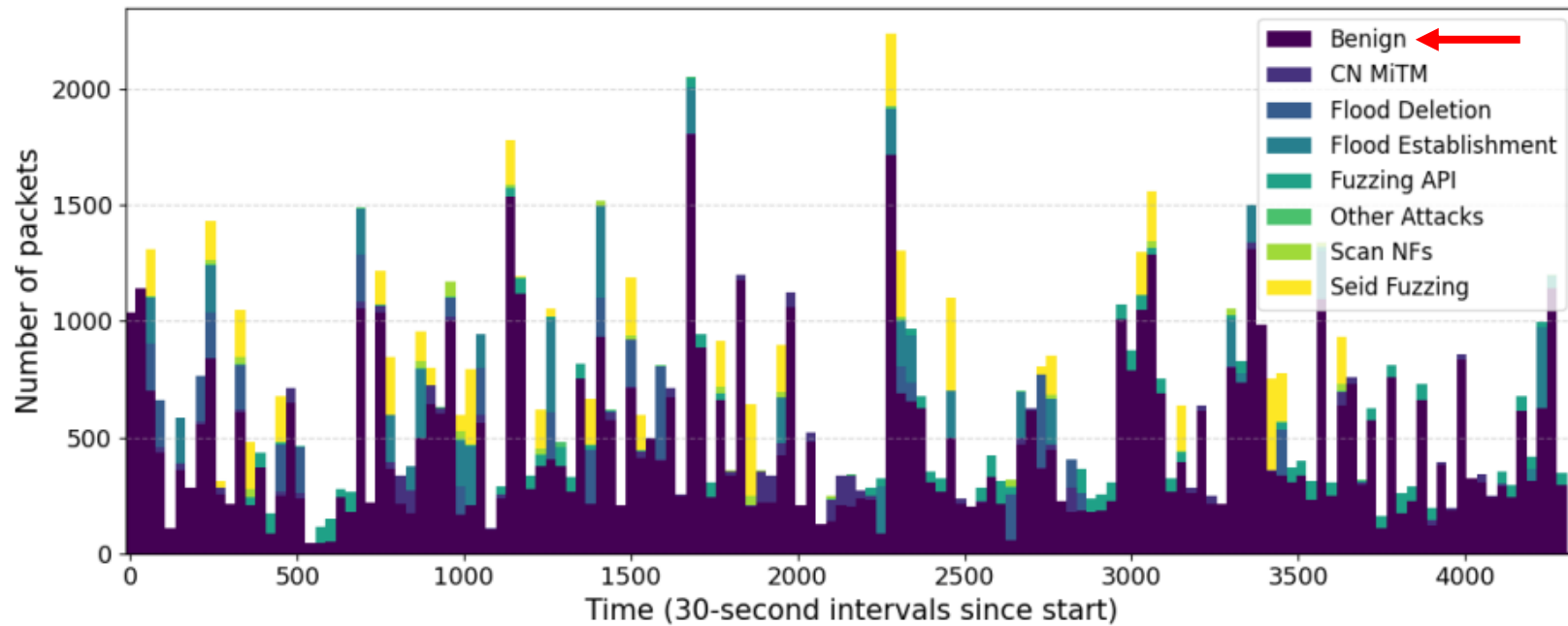
89% API Fuzzing message do not have semantically identical benign counterpart

Analyzing sequence diversity



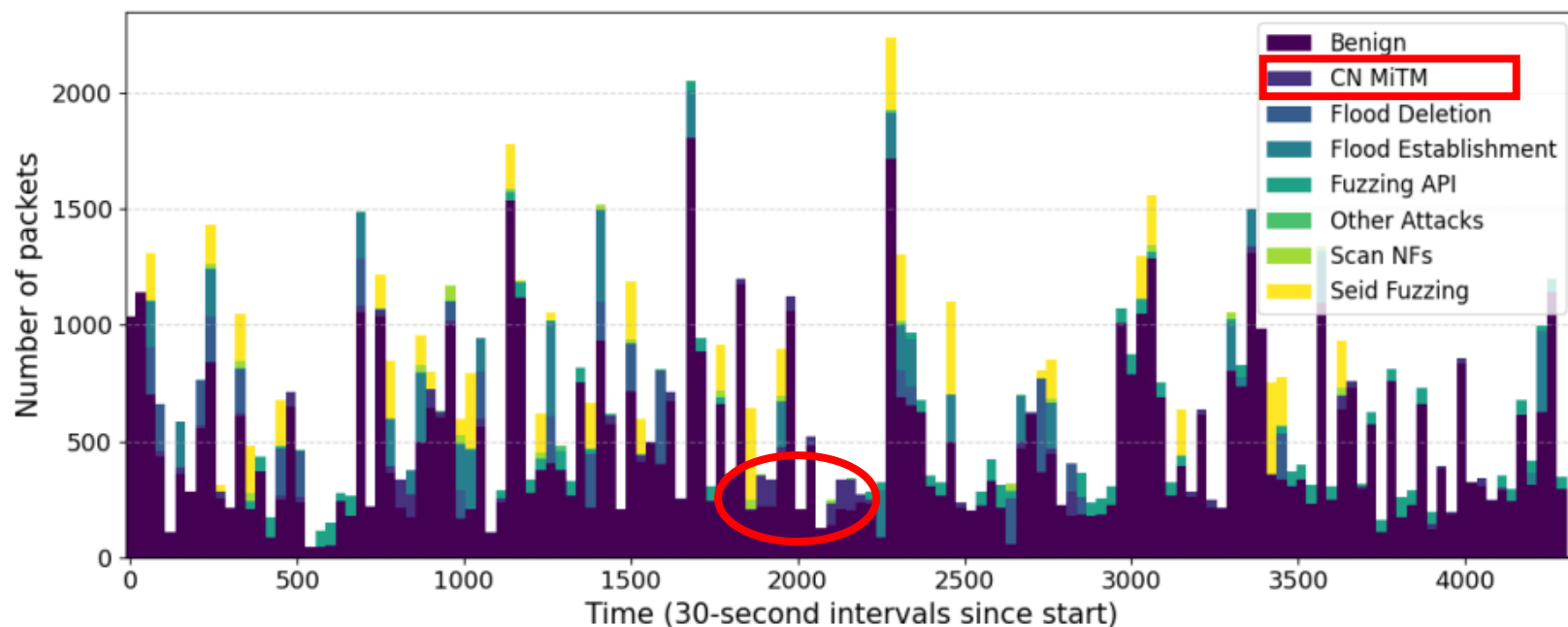
Malicious procedure	Detection Type
Applicative NF scanning	Repetition
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Establishment flooding	Repetition
Deletion flooding	Repetition
Session DoS	Repetition / Semantic
SEID fuzzing	Repetition
PFCP-in-GTP	Semantic
Uplink spoofing	Interactions

Analyzing sequence diversity



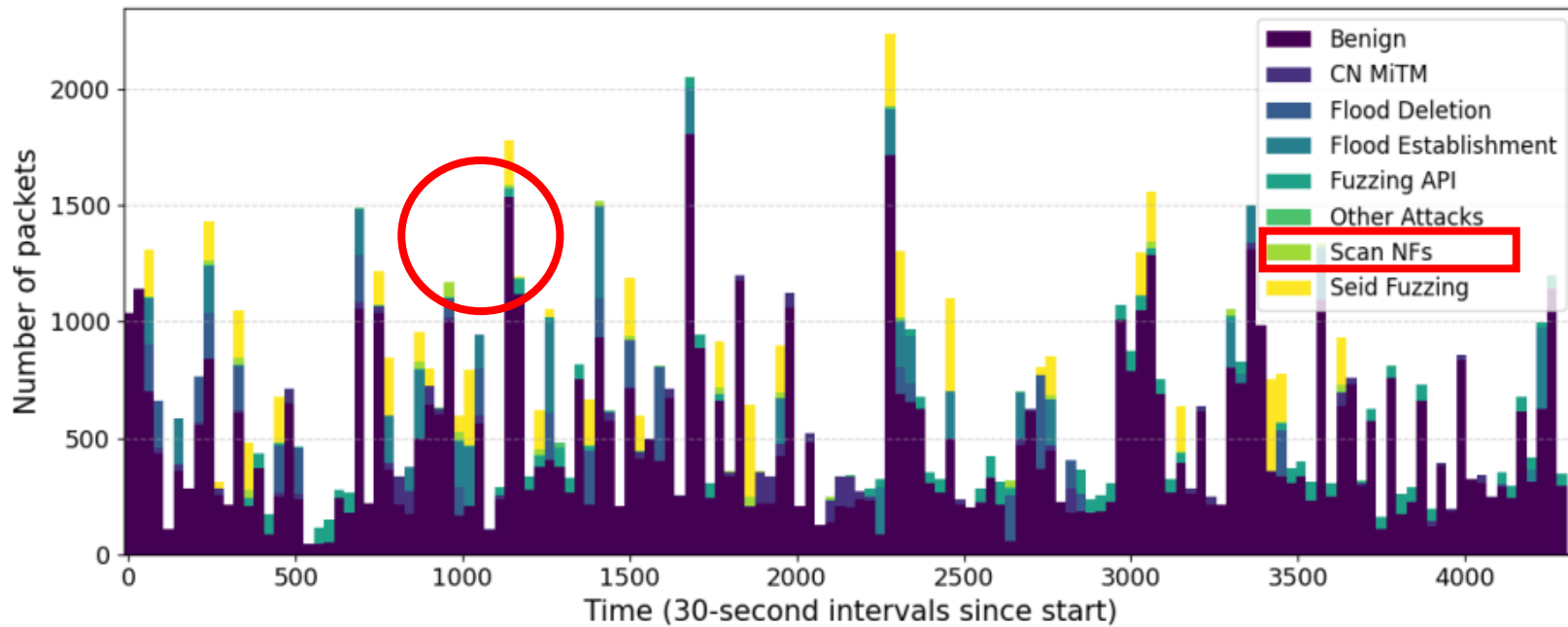
Malicious procedure	Detection Type
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PFCP-in-GTP	Semantic
Uplink spoofing	Interactions

Analyzing sequence diversity



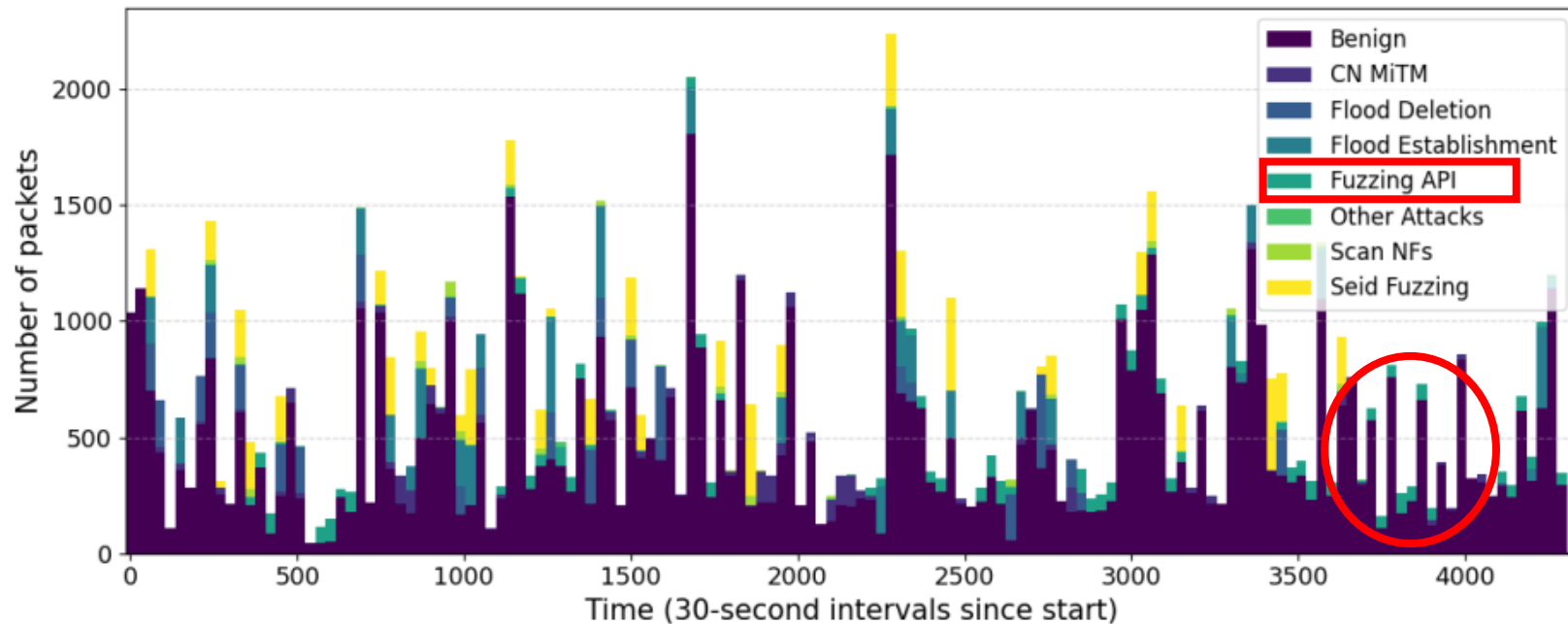
Malicious procedure	Detection Type
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Analyzing sequence diversity



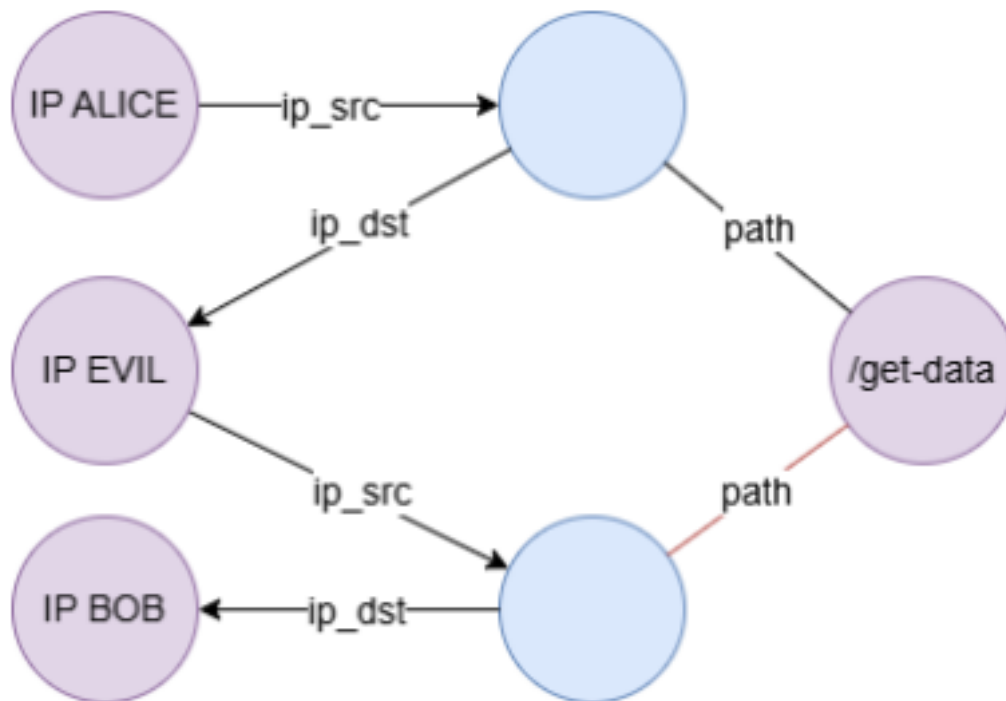
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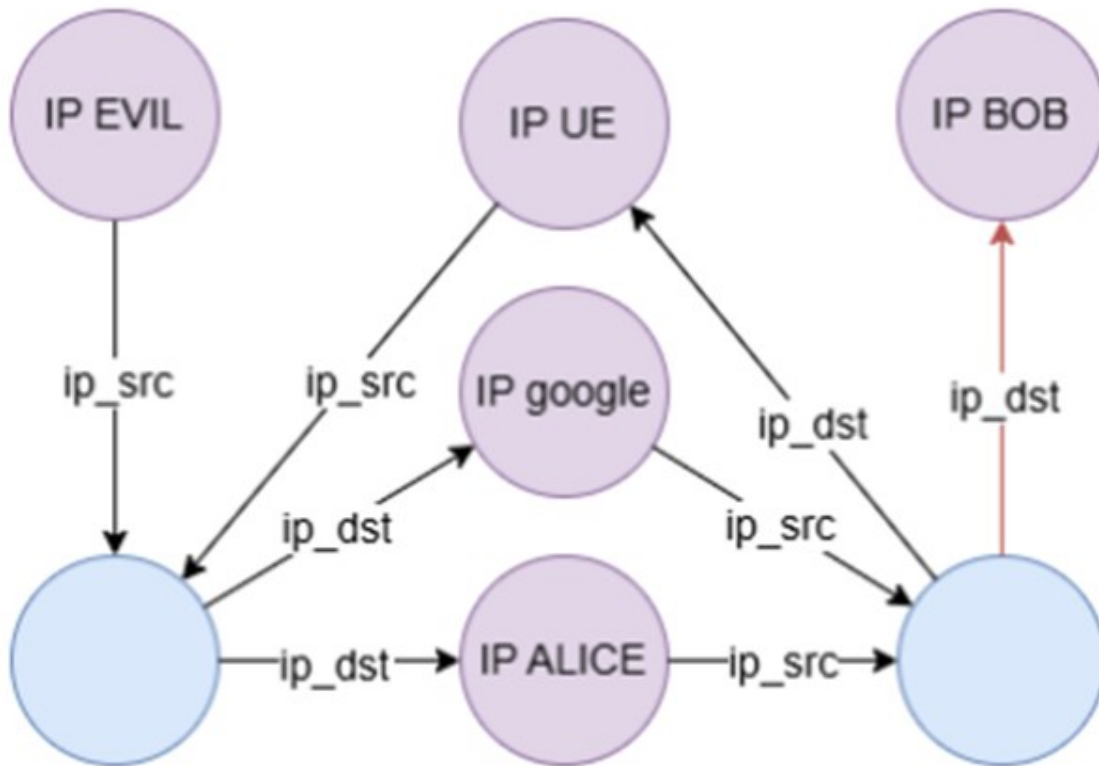
Analyzing interaction diversity



Malicious procedure	Detection Type
Applicative NF scanning	Repetition
API fuzzing	Repetition / Semantic
Man-in-the-middle in the CN	Interactions
Establishment flooding	Repetition
Deletion flooding	Repetition
Session DoS	Repetition / Semantic
SEID fuzzing	Repetition
PFCP-in-GTP	Semantic
Uplink spoofing	Interactions

4500 matches of redirection pattern

Analyzing interaction diversity



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Man-in-the-middle in the CN	Interactions
Establishment flooding	Repetition
Deletion flooding	Repetition
Session DoS	Repetition / Semantic
SEID fuzzing	Repetition
PFCP-in-GTP	Semantic
Uplink spoofing	Interactions

72 matches / 92 procedure execution (packet loss)