



Cybersecurity and Insider Threats

GNNs-Based Zero-Assumption Control-Flow Attestation

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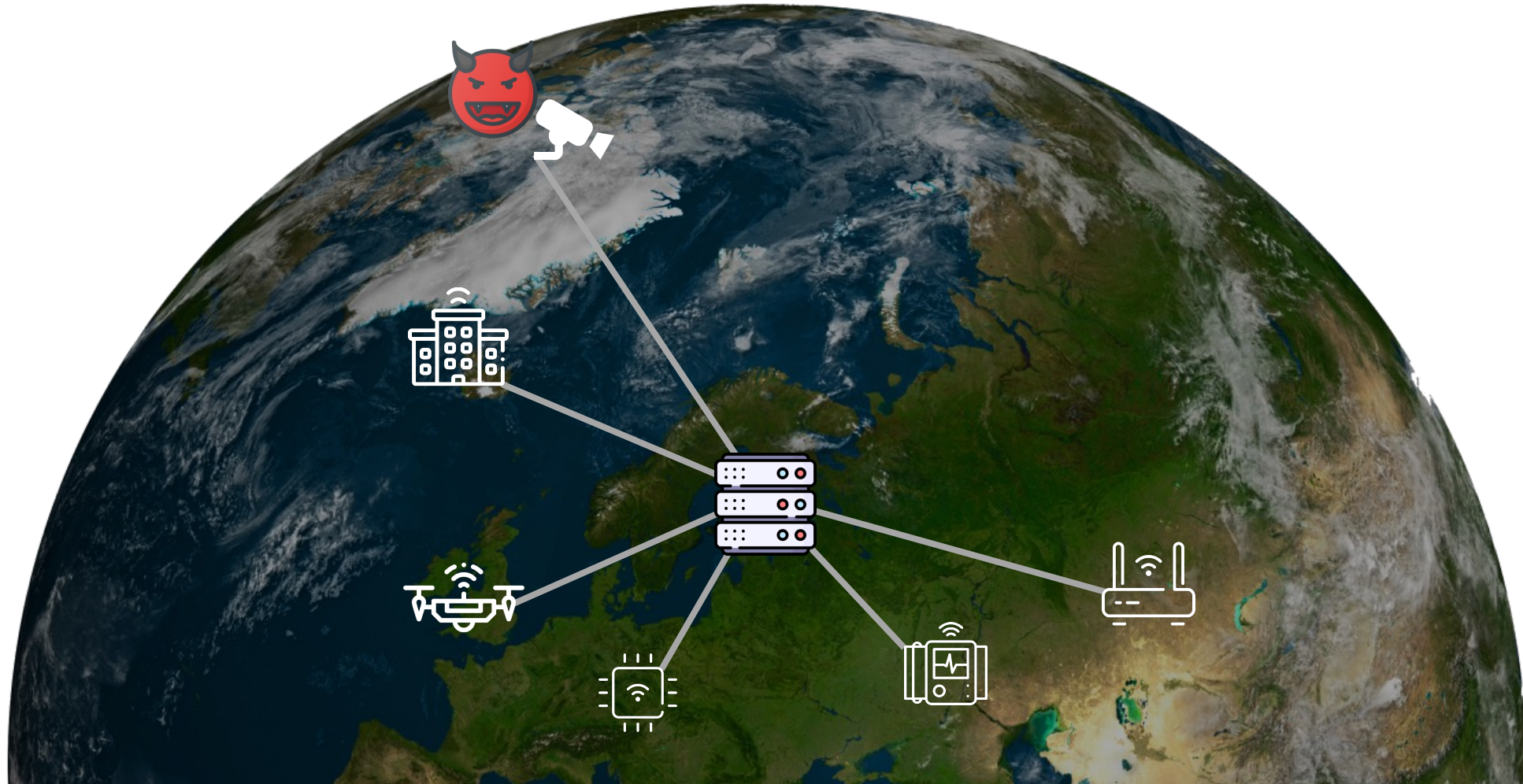
Technical University of Darmstadt, Germany

Webinar

Online, 31.05.2023

www.project-assured.eu

Why Attestation?

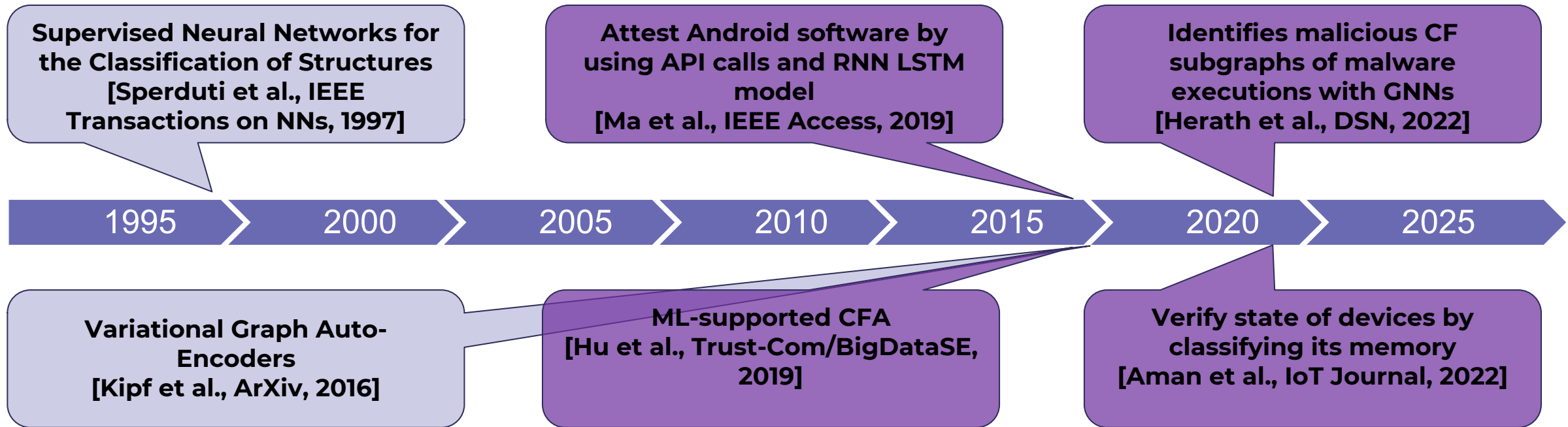


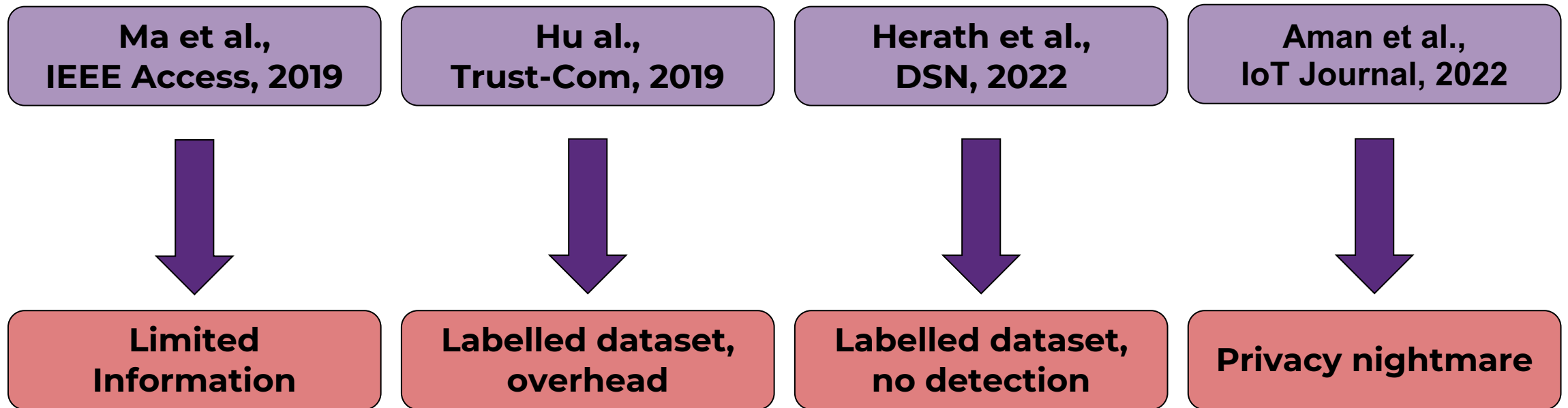
- Current approaches have **unrealistic assumptions**
 - Full Control-Flow Graph
 - Memory access
 - Custom hardware
- In real-world we cannot rely on any of these assumptions
 - **Extracted CFGs are incomplete → Machine Learning?**

Research Question

Is it possible to utilize Machine Learning on incomplete CFG for Control Flow Attestation?

Related Work





Software Instrumentalization

C-Flat

[Abera *et al.*, ACM SIGSAC, 2016]

RECFA

[Zhang *et al.*, ACSAC, 2021]

Extra Hardware

Lo-fat

[Dessouky *et al.*, DAC, 2017]

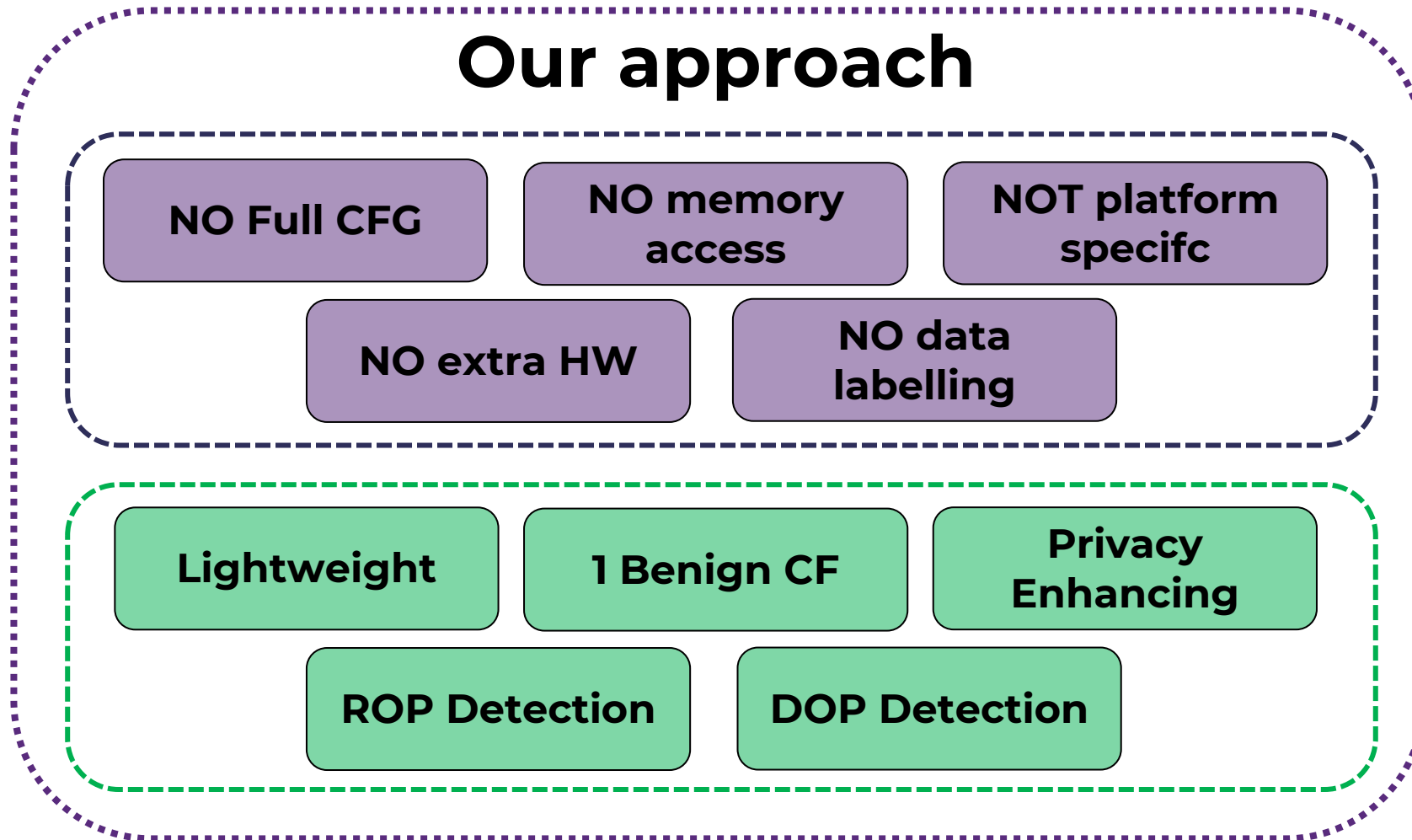
Atrium

[Zeitouni *et al.*, ICCAD, 2017]

Tiny-CFA

[De Oliveira Nunes *et al.*, DATE, 2021]

- **In general:** large database of full execution path or CF events



Our approach

NO Full CFG

**NO memory
access**

**NOT platform
specific**

NO extra HW

**NO data
labelling**

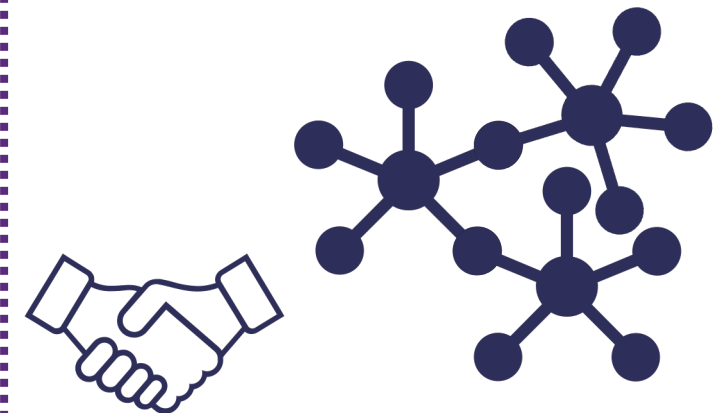
Lightweight

1 Benign CF

**Privacy
Enhancing**

ROP Detection

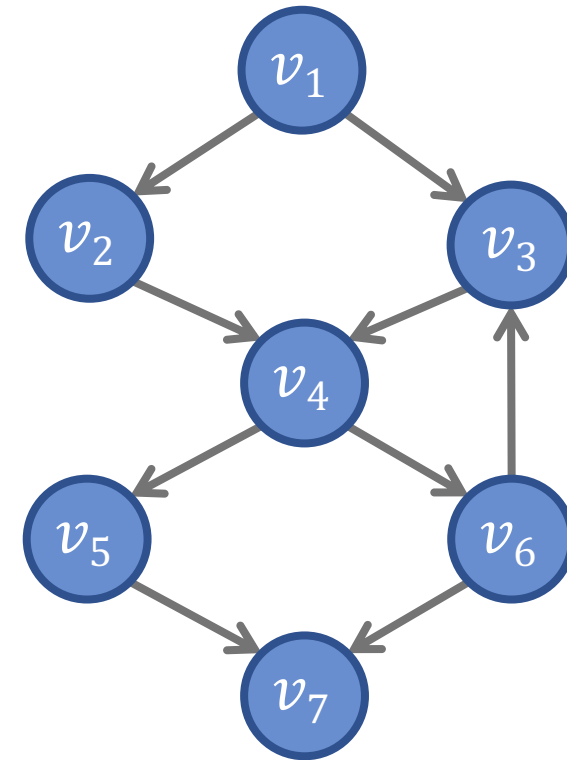
DOP Detection



**Unsupervised
Graph Neural
Networks**

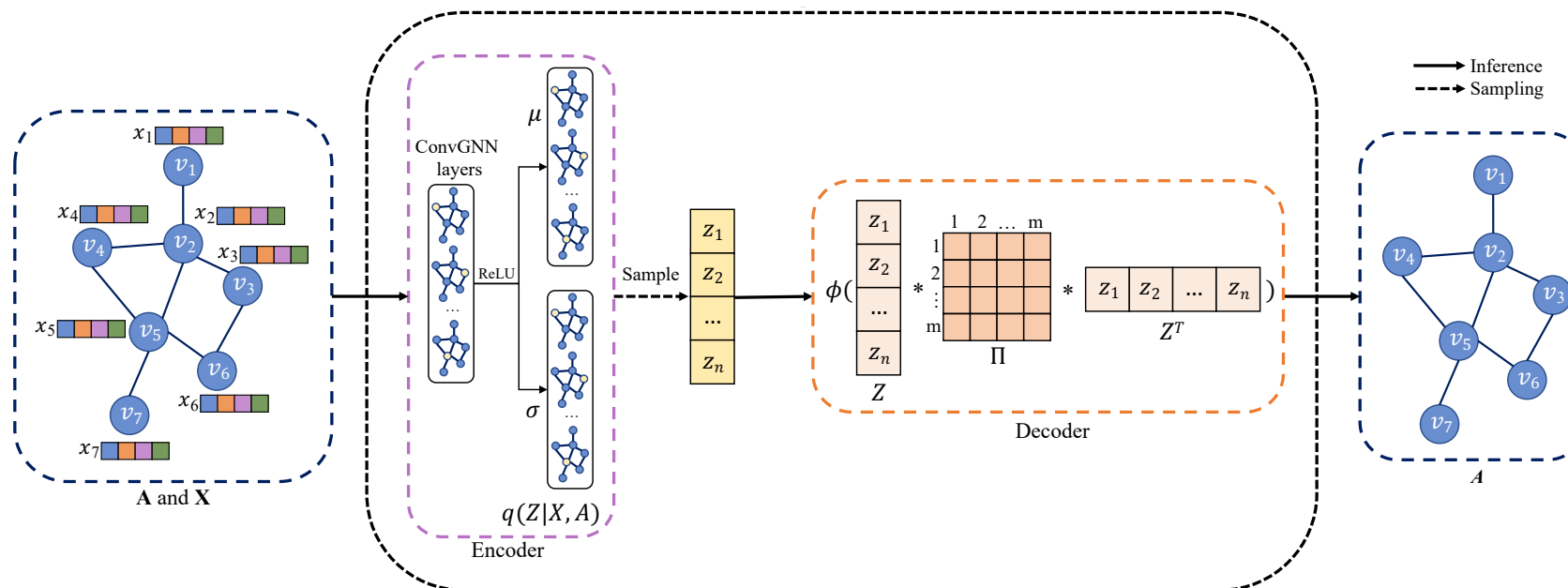
Background – CFA Attacks

- Two different benign executions in the CFG
- A **ROP attack** adds **extra transitions**
- A **DOP attack** **reuses benign transitions** but still alters the Control Flow

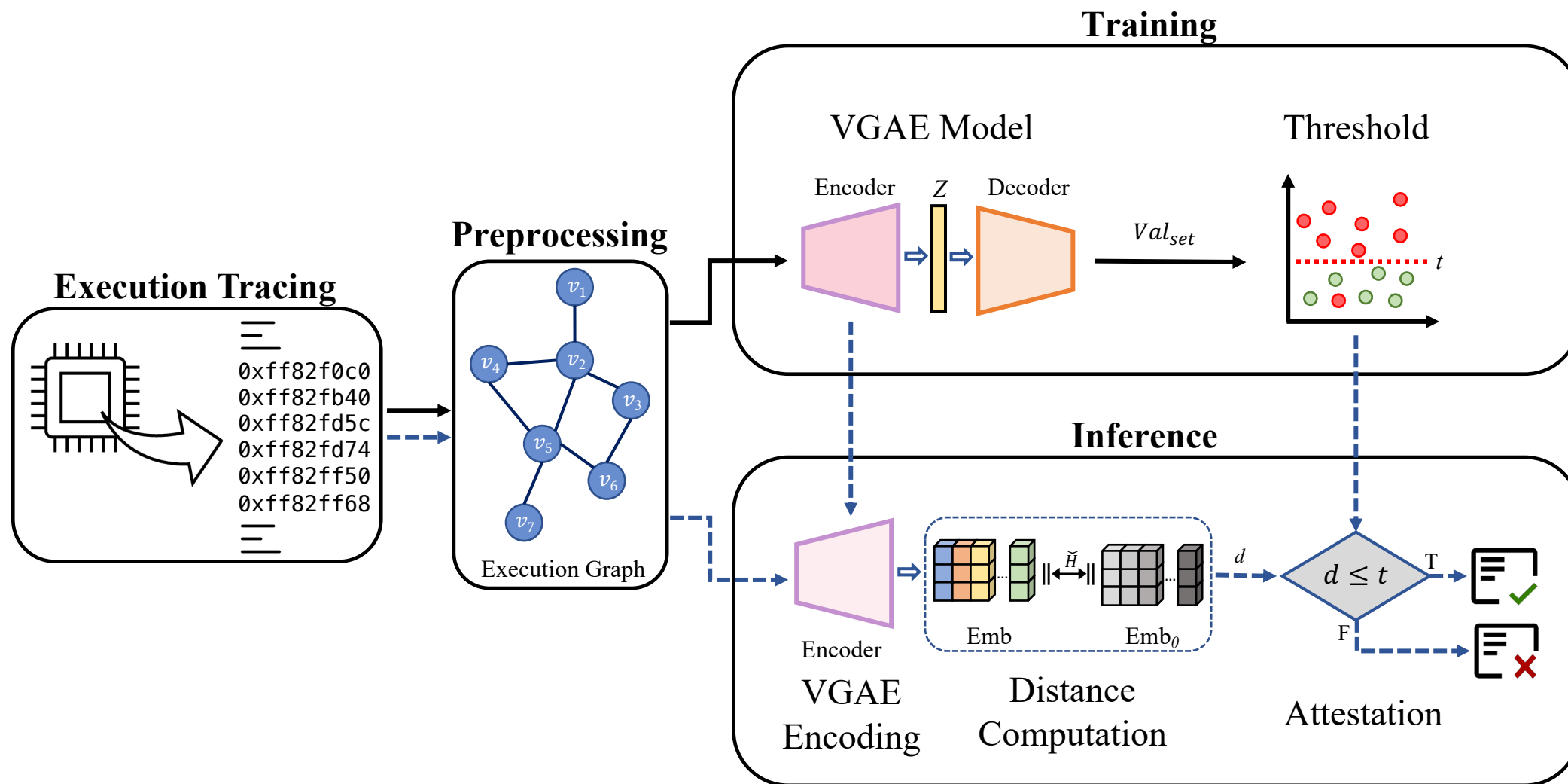


Control Flow Graph
(CFG)

- VGAEs are SotA **generative models** that are trained to learn to reconstruct input graphs
- Doing so it learns to capture **latent features** of the graph

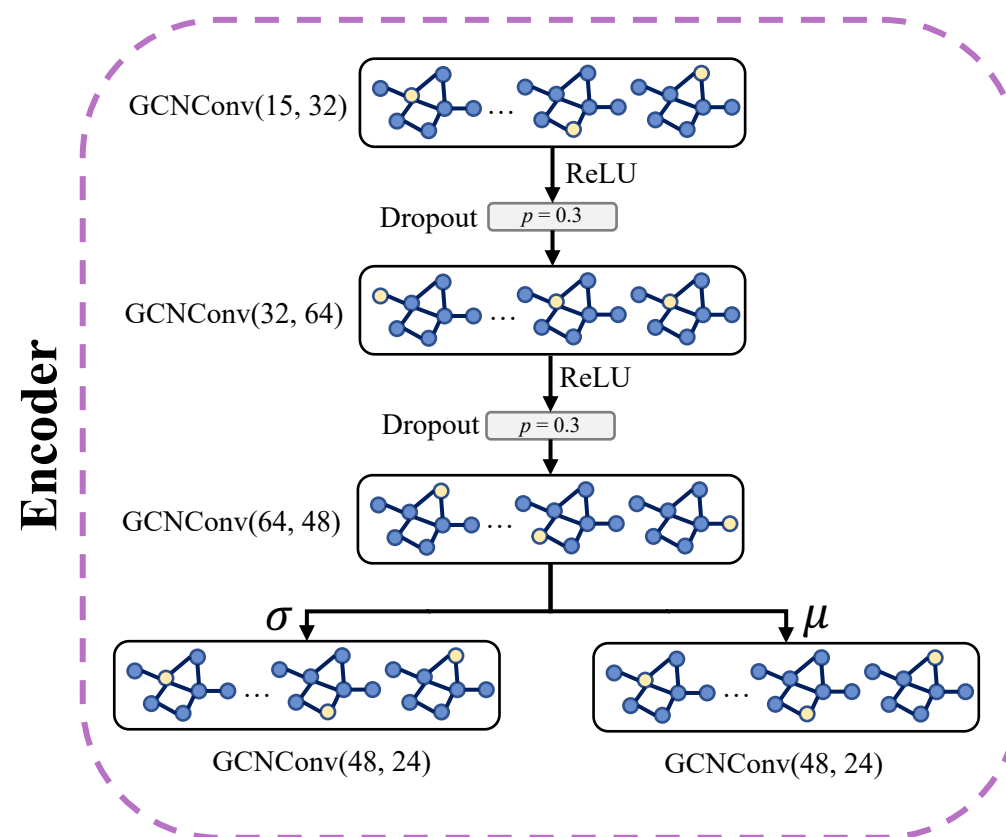


System Overview



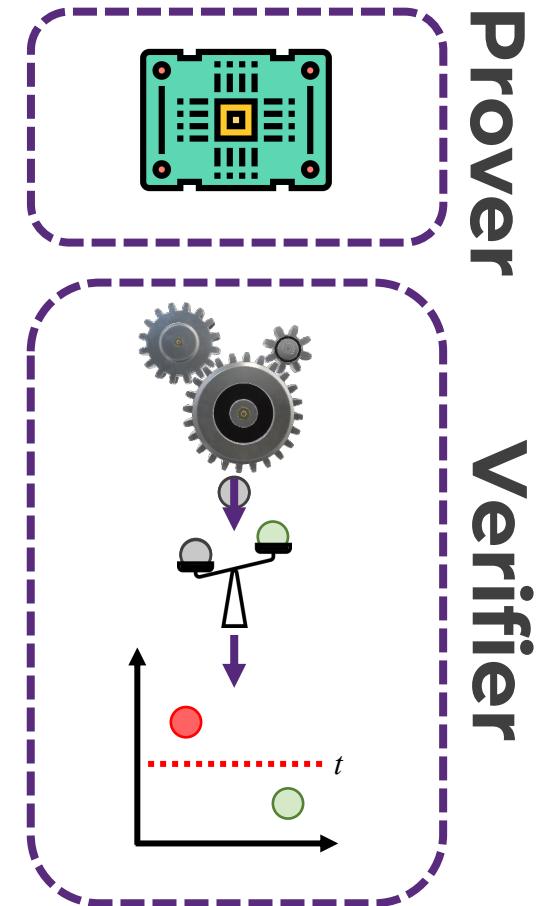
Implementation – VGAE Model

- From the encoder we obtain the **nodes' embeddings**
 - We can imagine them as a “fingerprint” of each node that is capturing its characteristics
- We designed our **deep Encoder** so to capture graphs' characteristics (e.g., connectivity, neighbours)
- **Regularization** through dropout layers and custom **decaying learning rate** schema
- The model counts **only 8,128 parameters**



Implementation - Attestation

- **Directed Hausdorff distance** between executions
- Attestation through **threshold test**
 - Calibrated on small benign validation set
- **Attack independent**



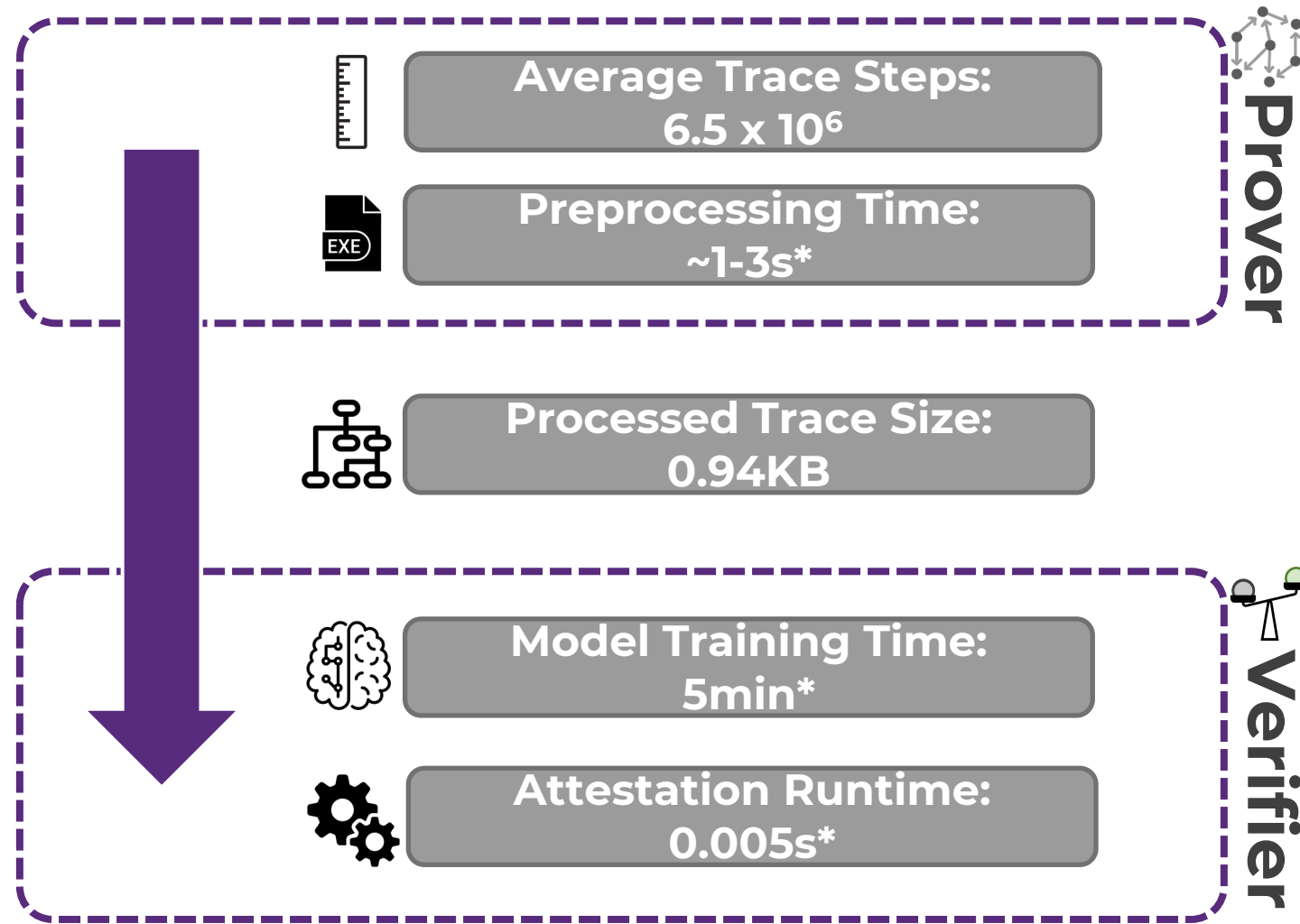
Evaluation

- Average F1-Score
 - ROP Attacks: 97.71%
 - DOP Attacks: 86.52%
- Average False-Positive-Rate of 3.63%

ROP Dataset	FPR	Pr.	Re.	F1	DOP Dataset	FPR	Pr.	Re.	F1
Diffie-Hellman	3.30	94.5	89.17	91.76	Diffie-Hellman	3.30	70.27	78.00	73.93
DES	7.72	96.93	99.37	98.14	DES	7.72	83.33	100.00	90.90
DESX	7.34	97.08	99.22	98.14	DESX	7.34	83.90	99.00	90.83
GOST	1.16	99.53	99.53	99.53	GOST	1.16	94.00	70.15	80.34
AES	0.39	99.84	98.74	99.29	AES	0.39	97.61	77.36	86.31
EmbenchIoT*	1.85	99.72	99.16	99.42	EmbenchIoT*	1.85	95.5	98.6	96.8
Ø	3.63	97.93	97.53	97.71	Ø	3.63	87.44	87.19	86.52

*EmbenchIoT includes 18 software

Evaluation: Performance



*Timings observed on Raspberry Pi 4B 2GB



THANKS



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