Towards Sustainable Security in Systems-of-Systems

GNNs-Based Zero-Assumption Control-Flow Attestation

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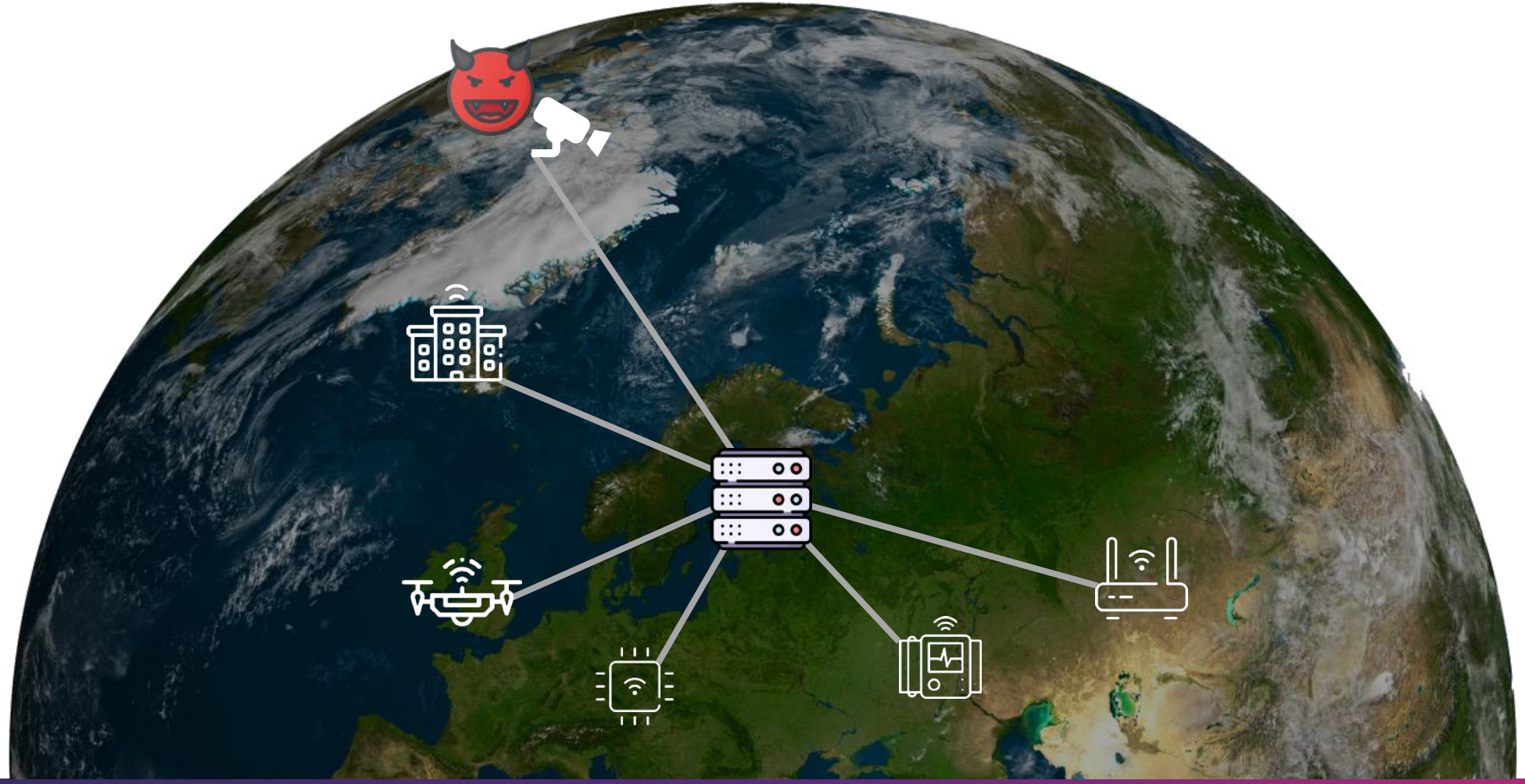
Why Attestation?



Motivation

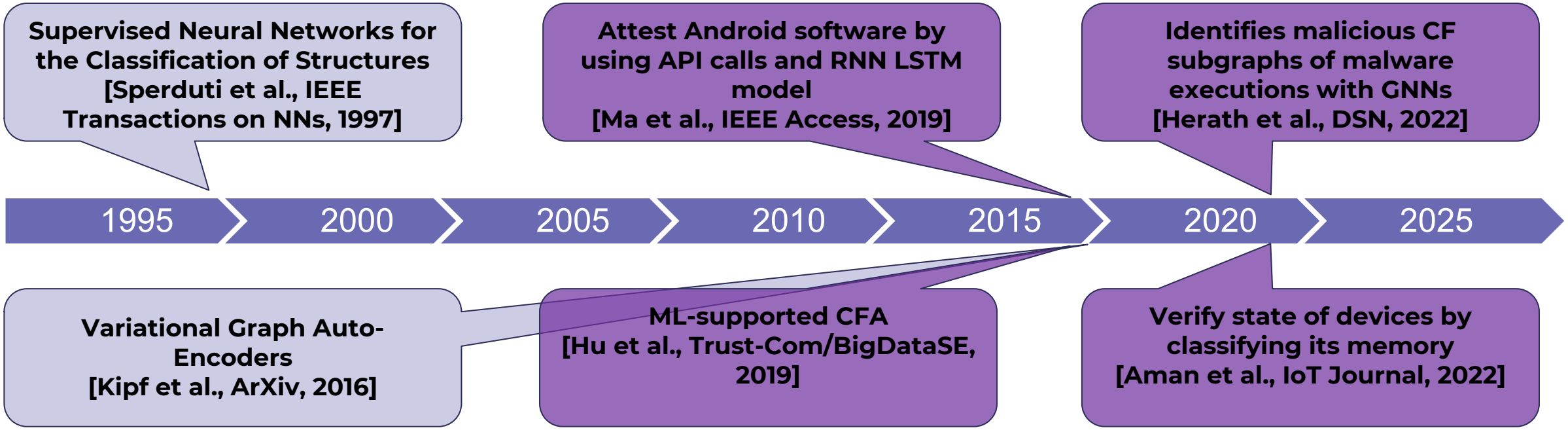
- Current approaches have **unrealistic assumptions**
  - Full Control-Flow Graph
  - Memory access
  - Custom hardware

- In real-world we cannot rely on any of these assumptions
  - **Extracted CFGs are incomplete → Machine Learning?**

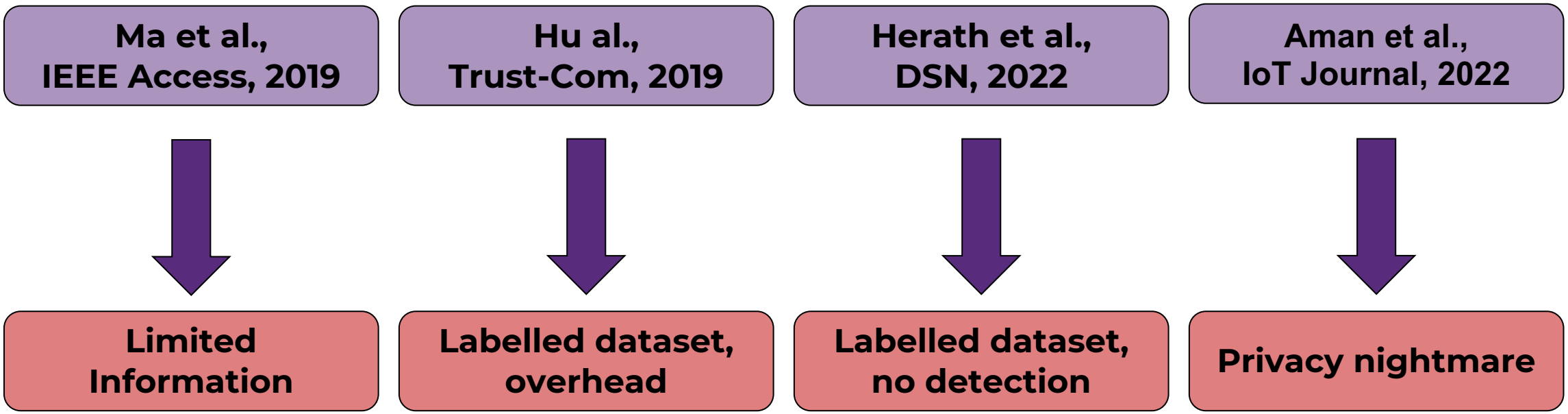
Research Question

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

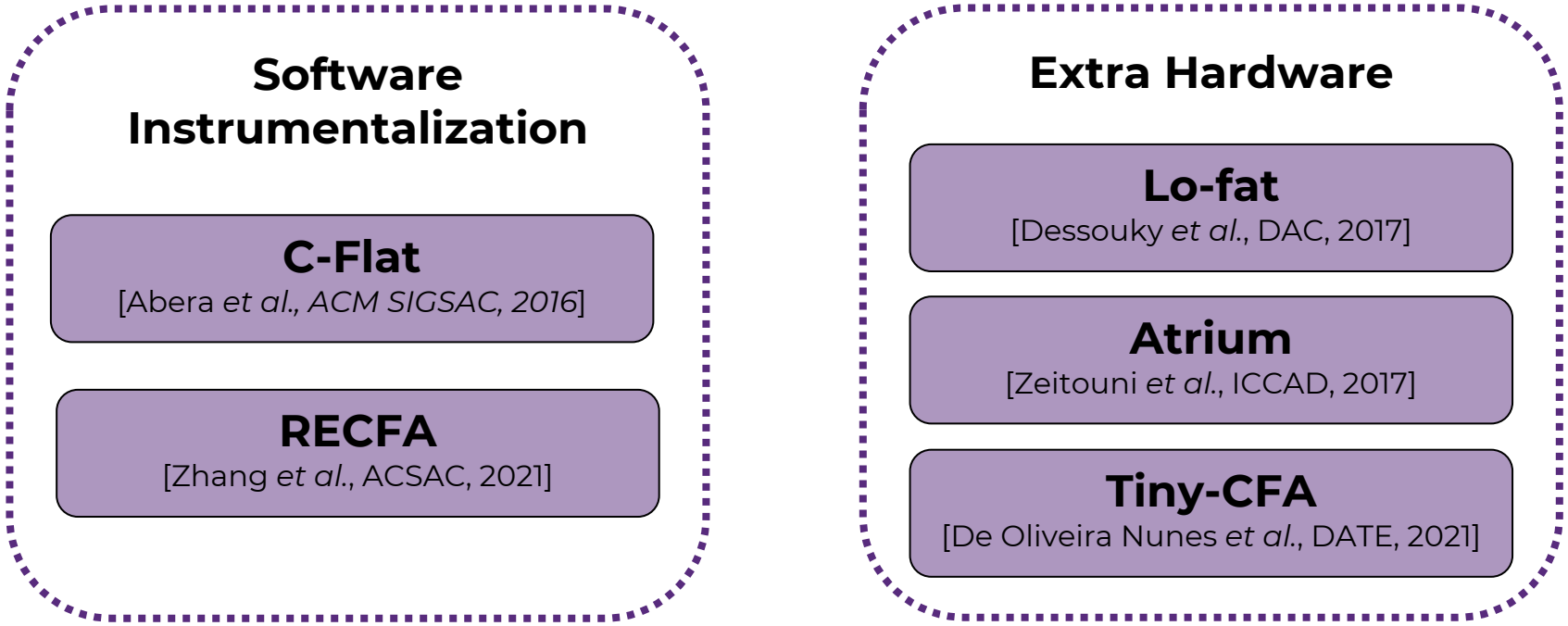
Related Work



State of the Art

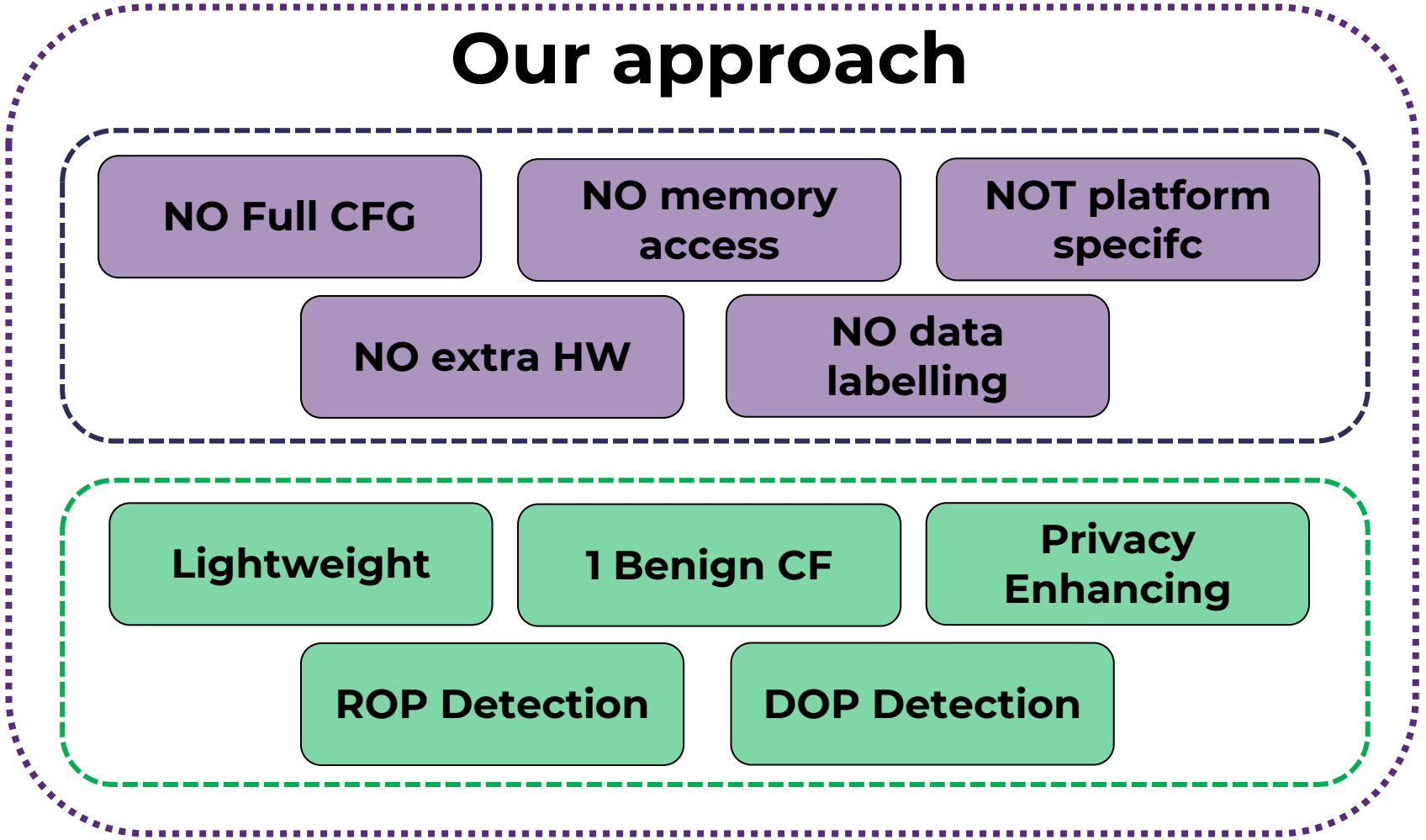


State of the Art – Not only ML



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

State of the Art – Not only ML

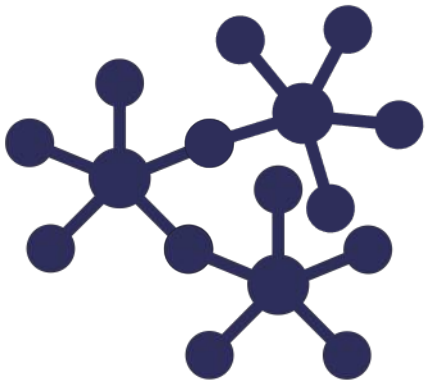


State of the Art – Not only ML

Our approach

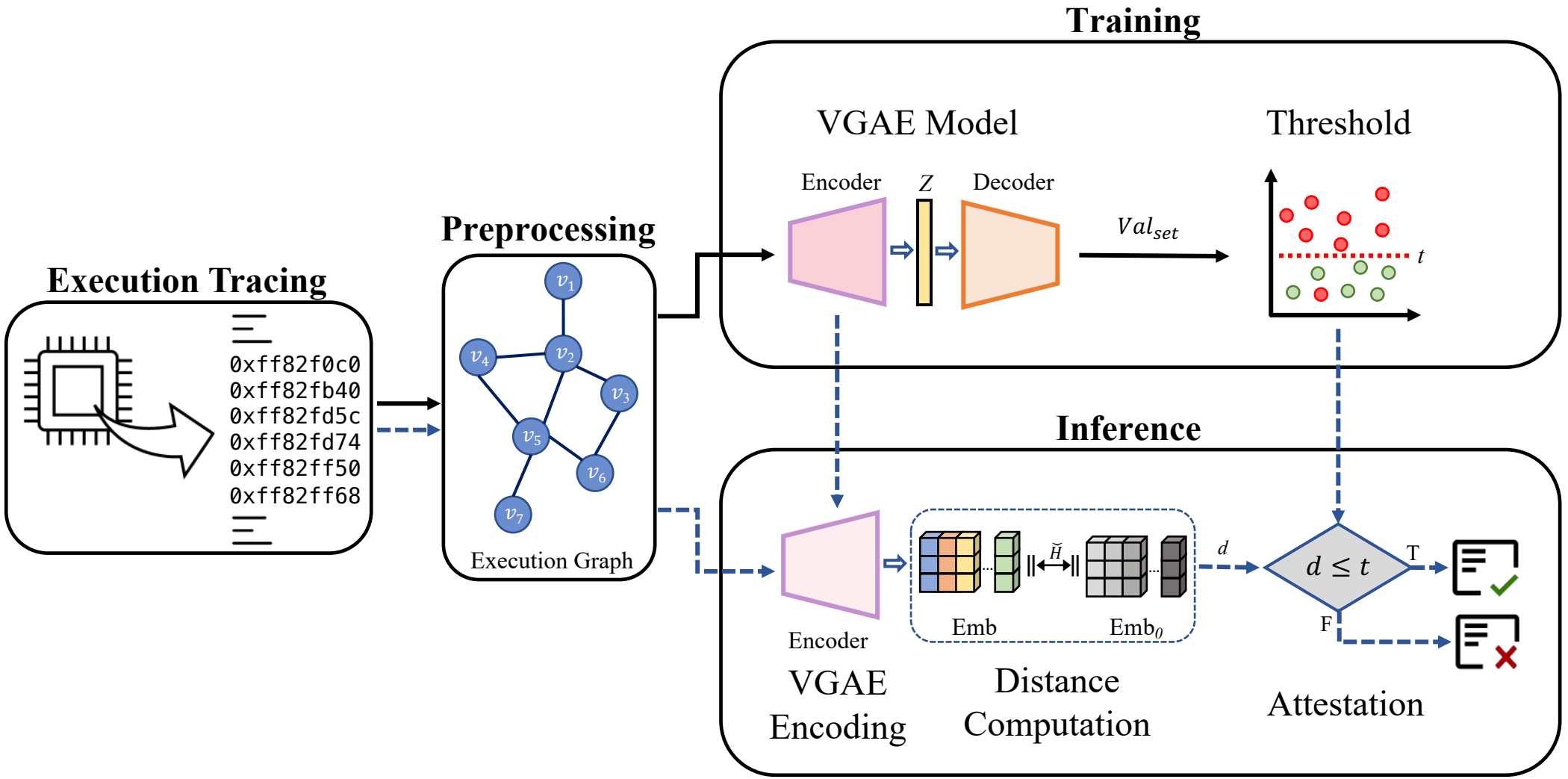
- NO Full CFG
- NO memory access
- NOT platform specifc
- NO extra HW
- NO data labelling

- Lightweight
- 1 Benign CF
- Privacy Enhancing
- ROP Detection
- DOP Detection



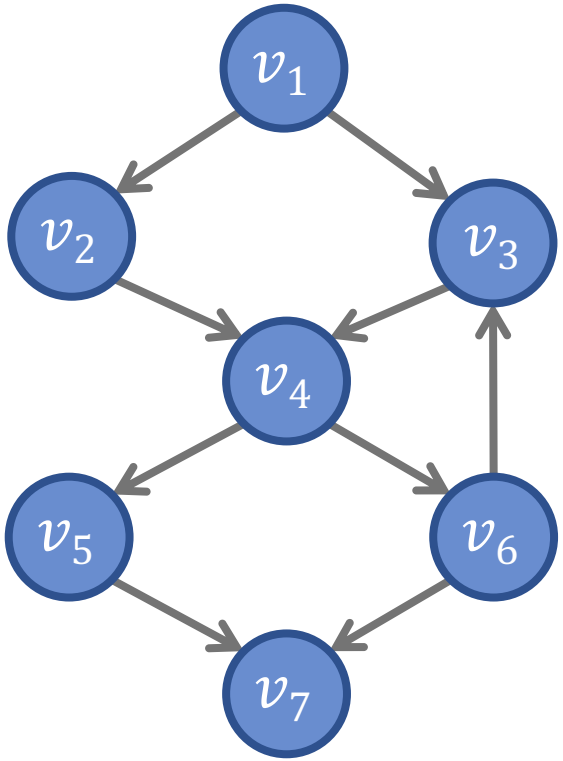
Unsupervised Graph Neural Networks

System Overview



Background – CFA Attacks

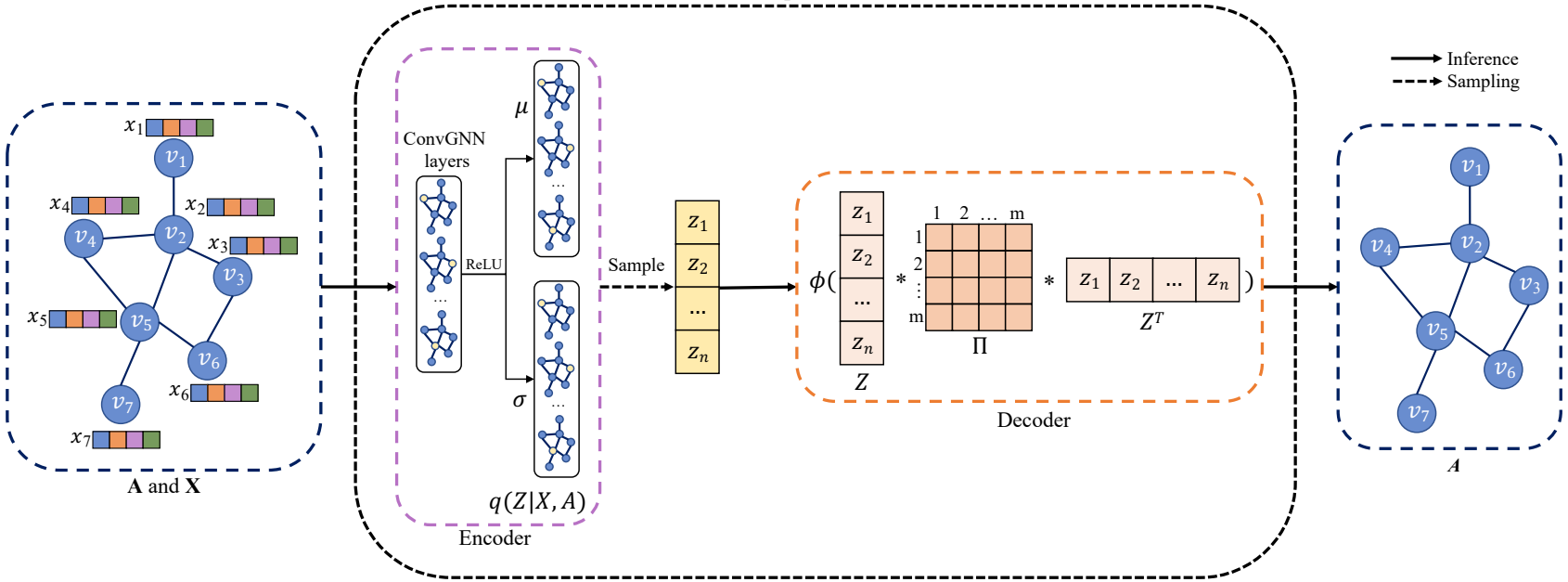
- Two different benign executions in the CFG
- A **ROP attack** adds **extra transitions**
- A **DOP attack reuses benign transitions** but still alters the Control Flow



Control Flow Graph (CFG)

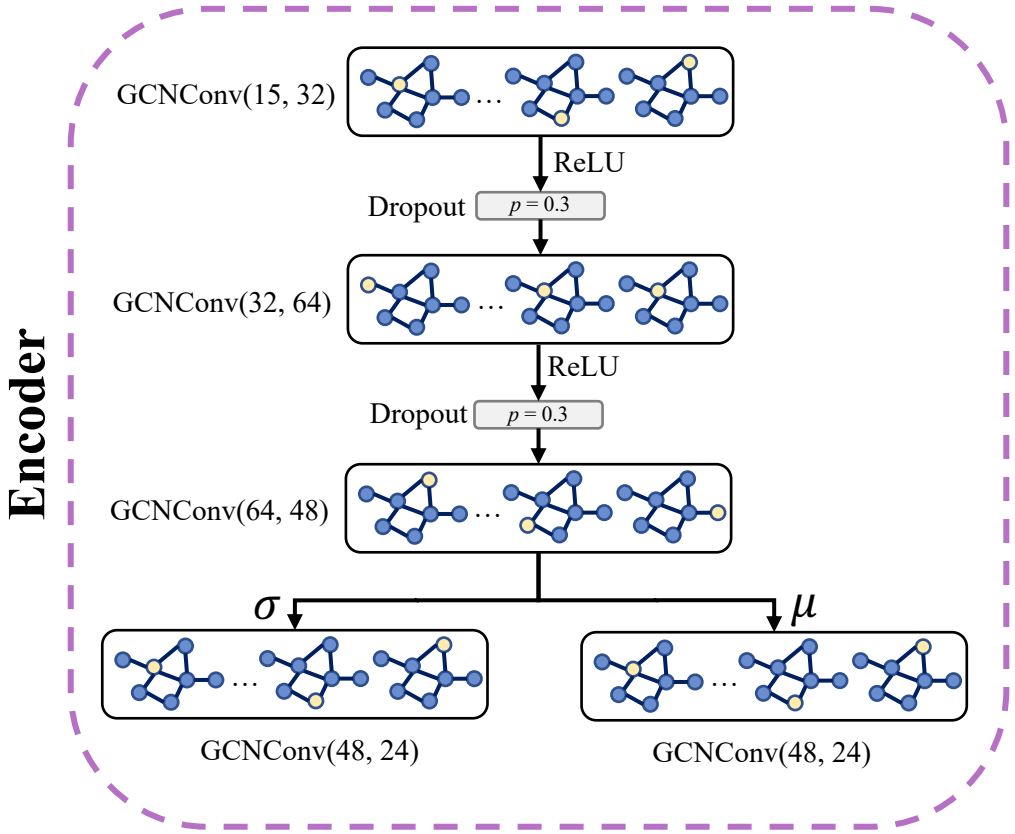
Background – VGAEs

- 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



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**

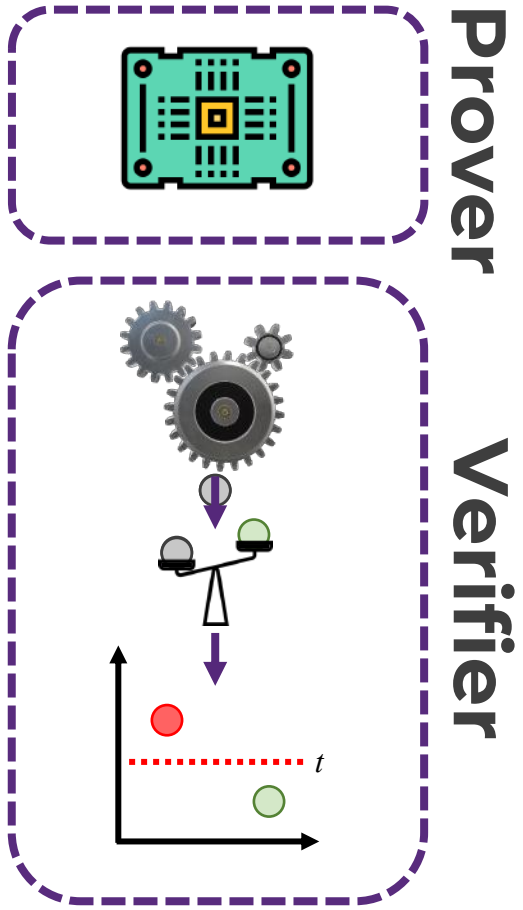


Implementation - Attestation

- **Directed Hausdorff distance** between executions

- Attestation through **threshold test**
  - Calibrated on small benign validation set

- **Attack independent**



Evaluation

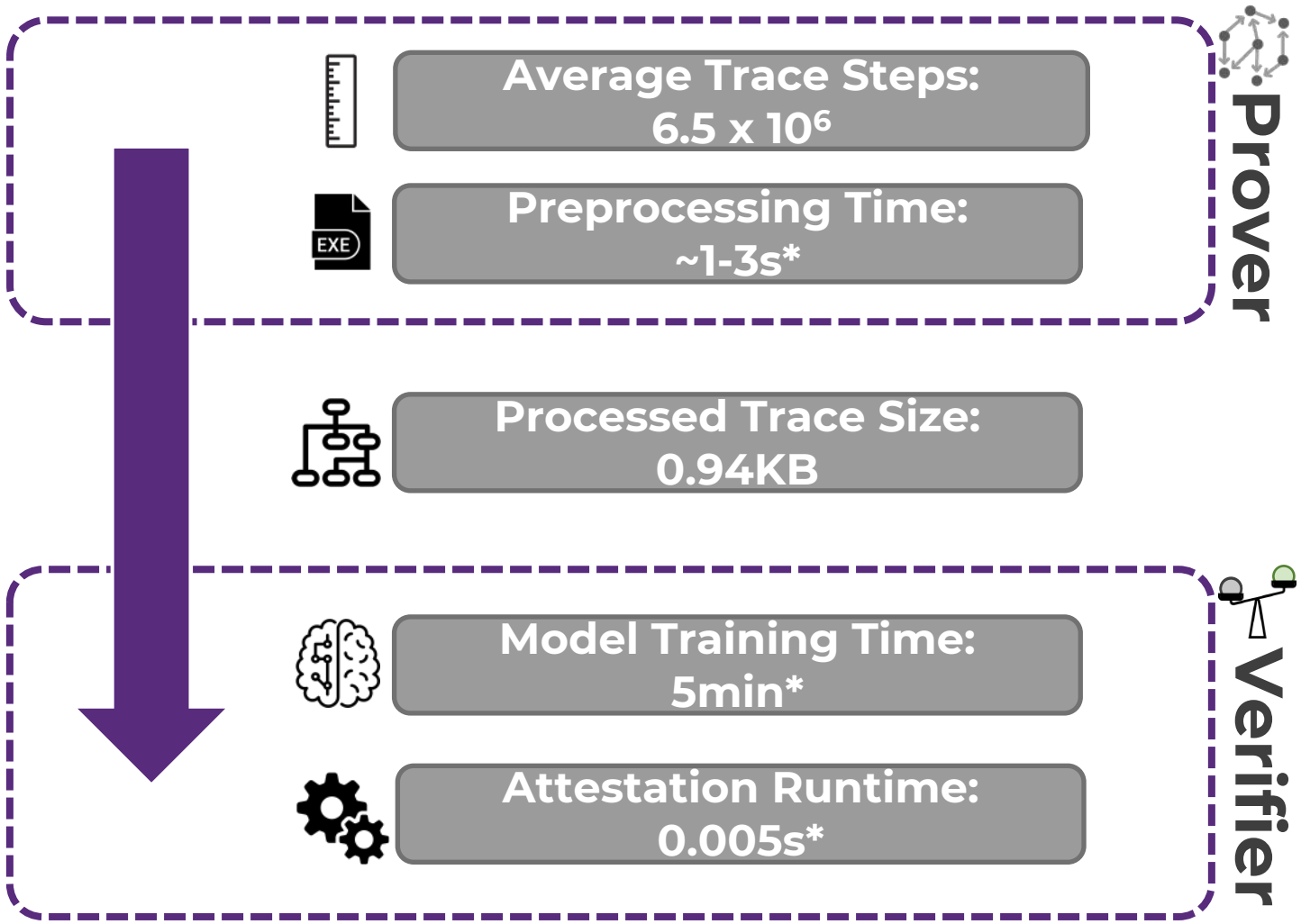
- Average F1-Score
  - ROP Attacks: 97.71%
  - DOP Attacks: 86.52%
- Average False-Positive-Rate of 3.63%

ROP Dataset	FPR	Pr.	Re.	F1
Diffie-Hellman	3.30	94.5	89.17	91.76
DES	7.72	96.93	99.37	98.14
DESX	7.34	97.08	99.22	98.14
GOST	1.16	99.53	99.53	99.53
AES	0.39	99.84	98.74	99.29
EmbenchIoT*	1.85	99.72	99.16	99.42
⌀	3.63	97.93	97.53	97.71

DOP Dataset	FPR	Pr.	Re.	F1
Diffie-Hellman	3.30	70.27	78.00	73.93
DES	7.72	83.33	100.00	90.90
DESX	7.34	83.90	99.00	90.83
GOST	1.16	94.00	70.15	80.34
AES	0.39	97.61	77.36	86.31
EmbenchIoT*	1.85	95.5	98.6	96.8
⌀	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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