Towards Context-aware Intrusion Detection in Individual-oriented Information Systems: **An Empirical Study on Android Malware**

Paper at the 21st International Conference on Network and Service Management (CNSM2025), Bologna, Italy

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ICO Annual Scientific Day, 05/12/2025

Outline

I. Background

II. State of The Art

III. Proposed framework

IV. Evaluation

V. Conclusion

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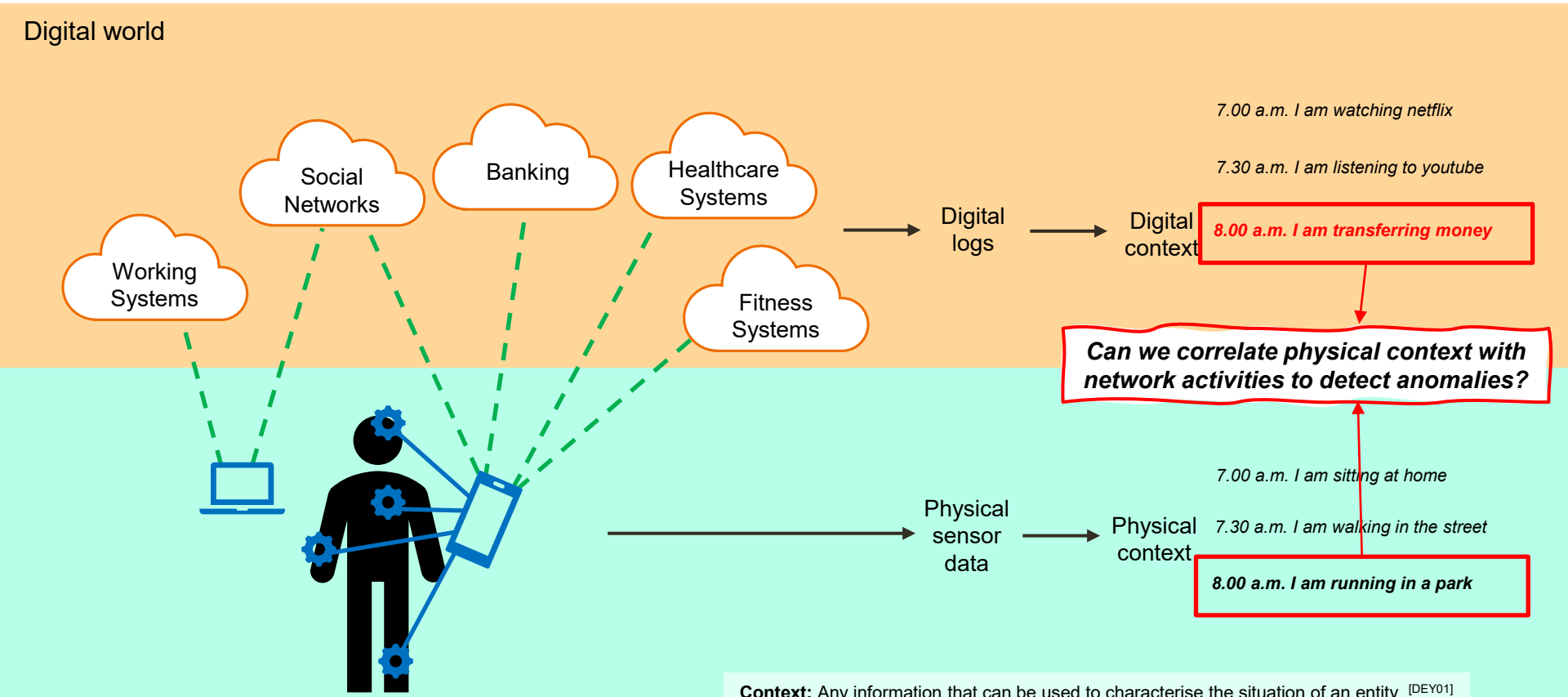
Outline

Background: Physical vs Digital context



Context: Any information that can be used to characterise the situation of an entity. [DEY01]

[DEY01] Dey, Anind K. "Understanding and using context." *Personal and ubiquitous computing* 5 (2001): 4-7.

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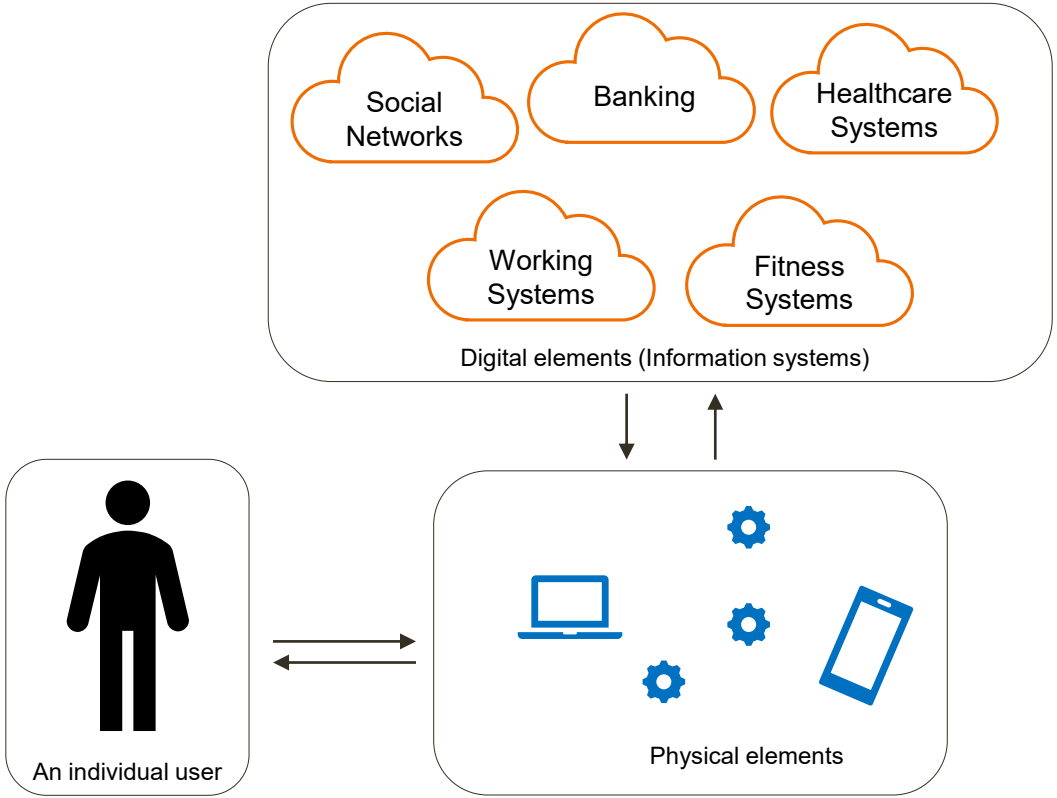
Individual-oriented Information System (IIS)



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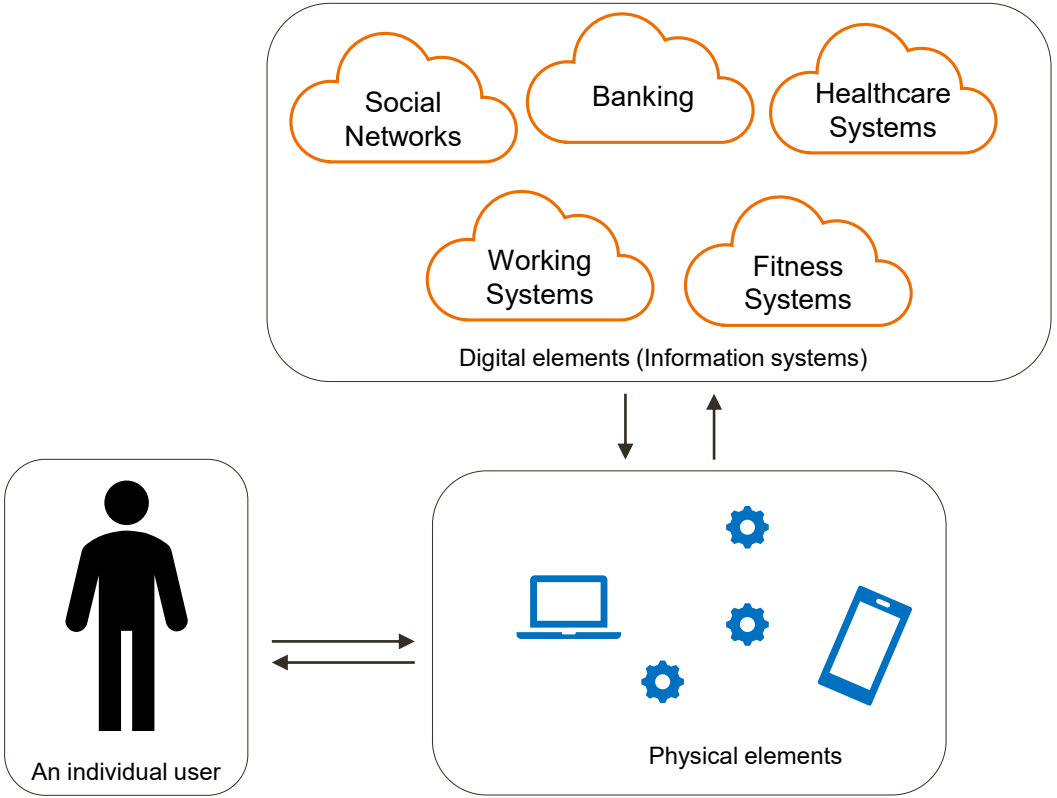


Limitations of security solutions in the literature

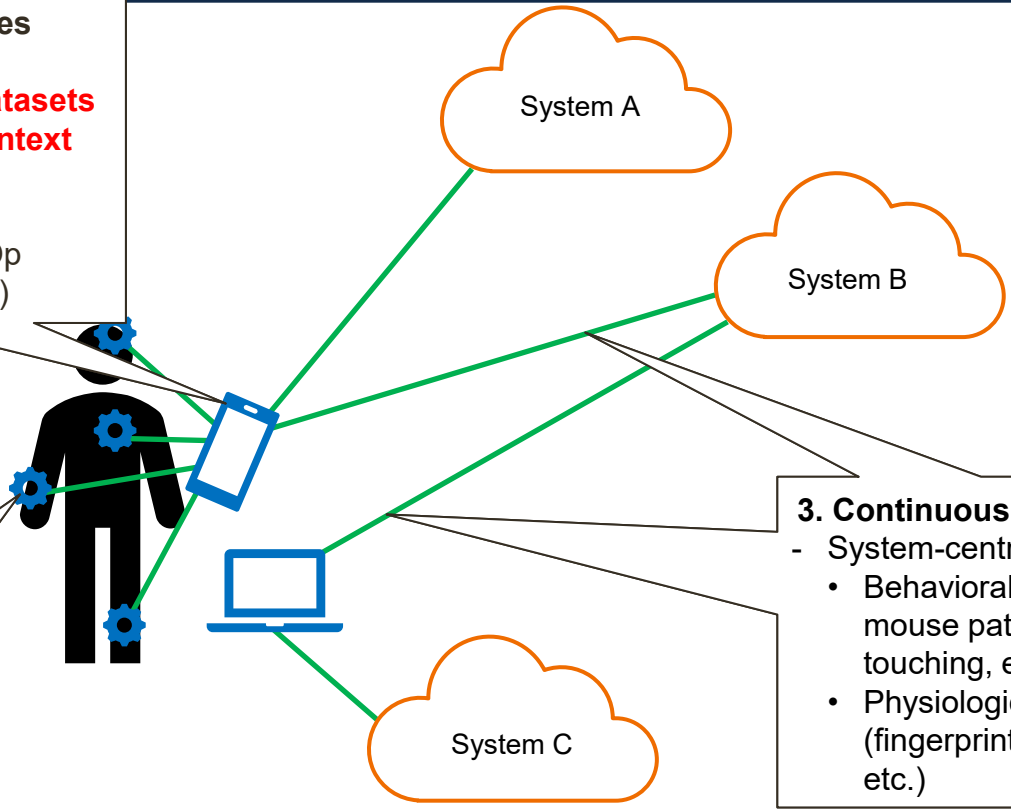
- System-specific
  - Require specific integration between client and server components
- Device-specific
  - Intrusive control and management
- ***Fail to protect*** against attacks where the adversary has sufficient knowledge to bypass these isolated solutions

The IIS considers the global context (digital + physical) of a user

SoTA: User physical contextual data in security solutions

1. IDS in mobile devices

- Network-based IDS
  - **Neither studies nor datasets available with user context**
- Host-based IDS
  - Device-centric
  - Device context (CPU, Op codes, permissions, etc)



2. WBAN Security

- User physical data (biometrics) are used
  - Crypto Key management
  - Authentication

  ⇒ To protect WBAN systems

3. Continuous Authentication

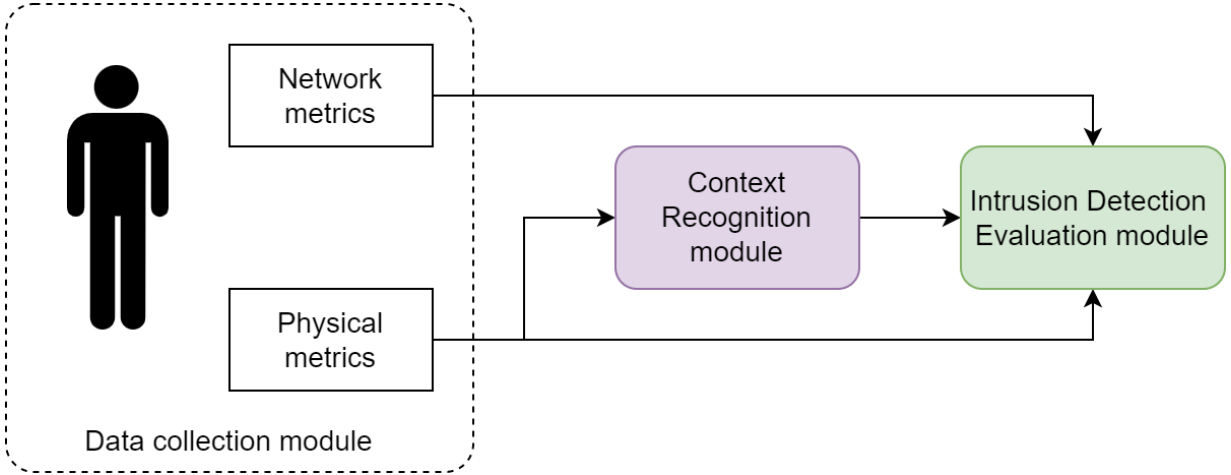
- System-centric, leveraging
  - Behavioral data (key stoke, mouse pattern, gait, touching, etc.)
  - Physiological data (fingerprint, iris, blood, etc.)

Research Question

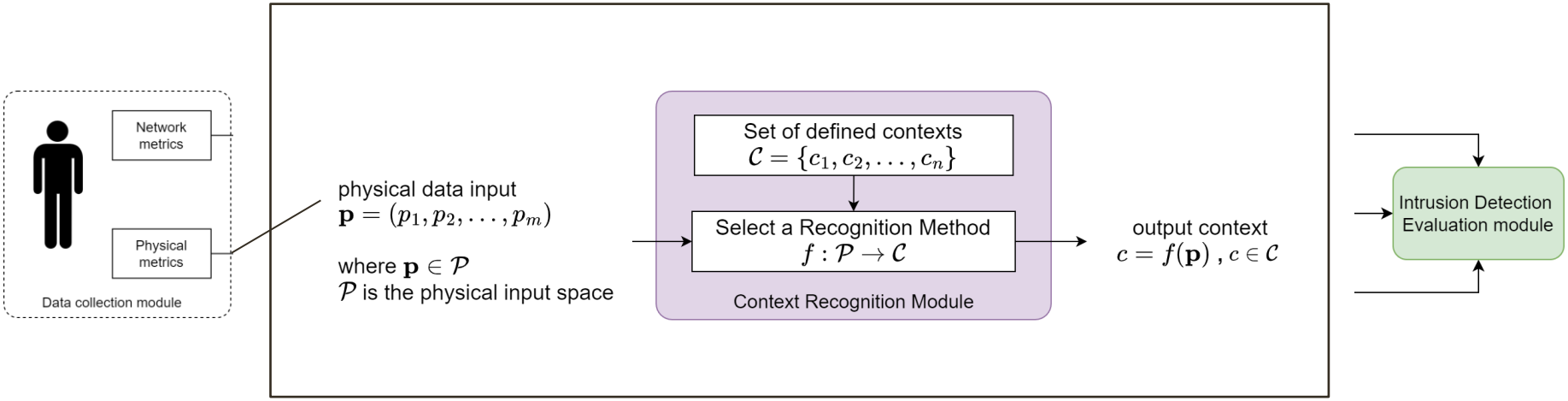
*Can a user's **physical contextual data** enhance the performance of **network intrusion detection**?*

Outline

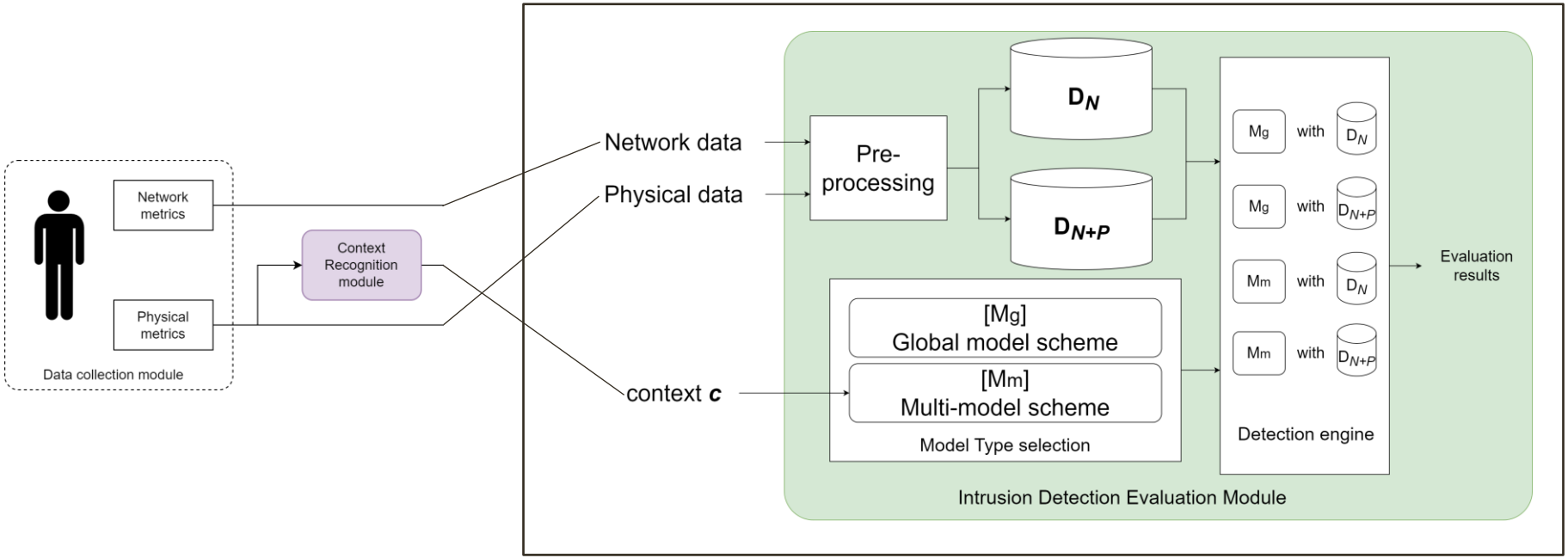
Overview


Network metrics
Physical metrics
Data collection module
Context Recognition module
Intrusion Detection Evaluation module

Context Recognition Module

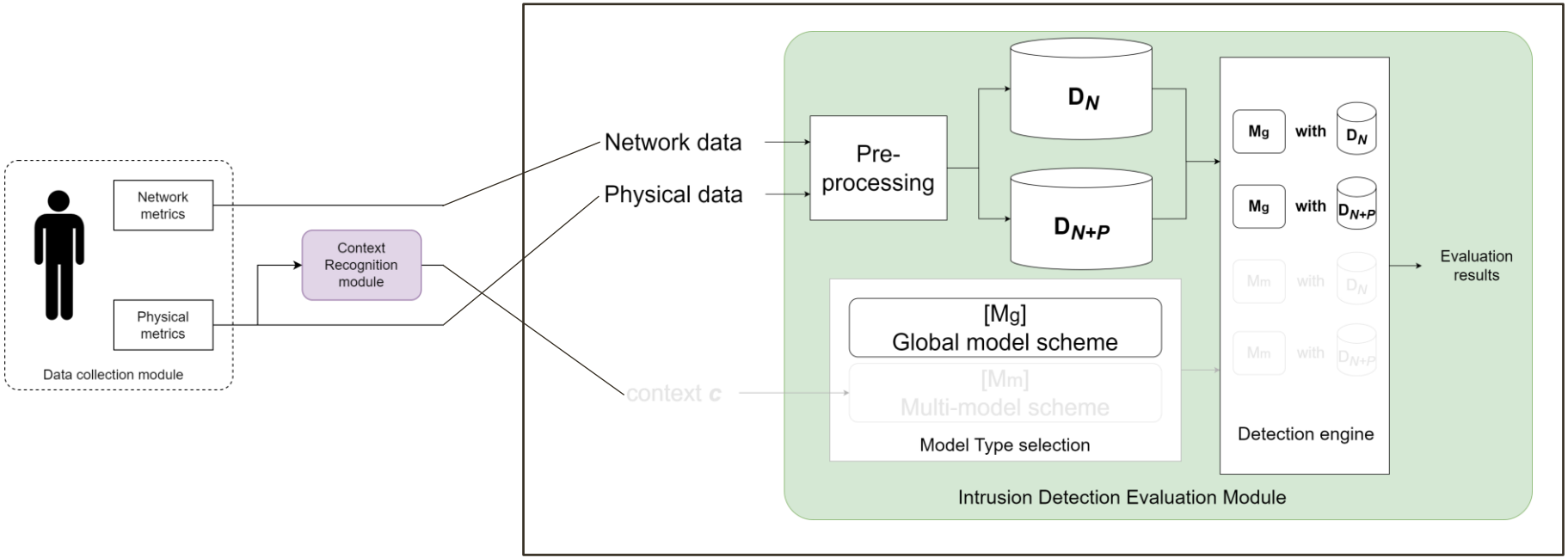


Intrusion Detection Evaluation Module



D_N: Dataset with network-only features (netflow-based features)
D_{N+P}: Dataset with network + physical features (accelerometer, ambient light, user speed)

Evaluation Scope



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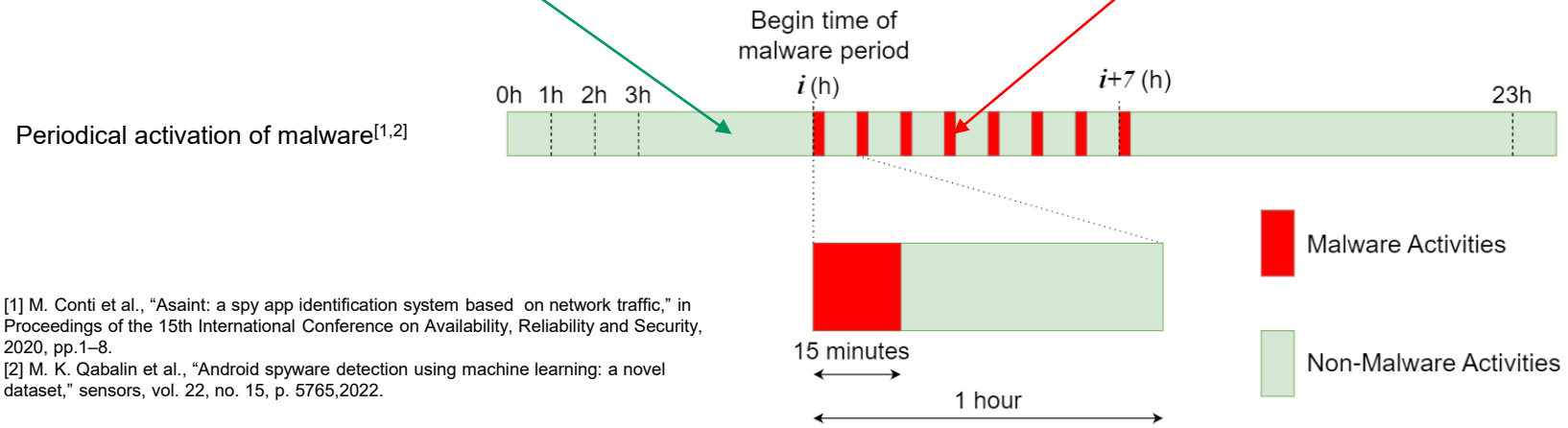
Dataset

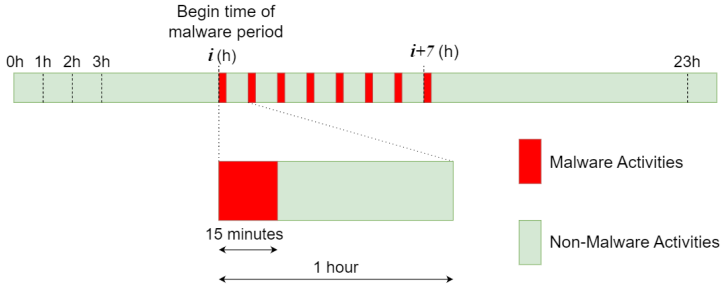
Benign data
Our in-situ data collection experiment
User's daily activities (2 x 24h),
From a personal smartphone

Malware data
Extracted from CIC-AndMal2017 dataset
- 5 Adware families
- 8 captures / family
- 15 minutes / capture



[1] M. Conti et al., "Asaint: a spy app identification system based on network traffic," in Proceedings of the 15th International Conference on Availability, Reliability and Security, 2020, pp.1–8.
[2] M. K. Qabalin et al., "Android spyware detection using machine learning: a novel dataset," sensors, vol. 22, no. 15, p. 5765,2022.

Injection and Evaluation Pipeline



Imbalanced dataset

With each malware in [Ewind, Feiwo, Gooligan, Kemoge, Youmi]:

Inject 8 captures starting from hour ***i*** (***i*** = 0, 1,.., 23)

With each injection: Do the detection evaluation

Repeat 10 times:

Randomly split the dataset into train/validate/test set

Create a machine learning model (**XGBoost**)

Hyper-parameter turning

Cross Validation

Record the evaluation metric (**PR AUC**) on testing set

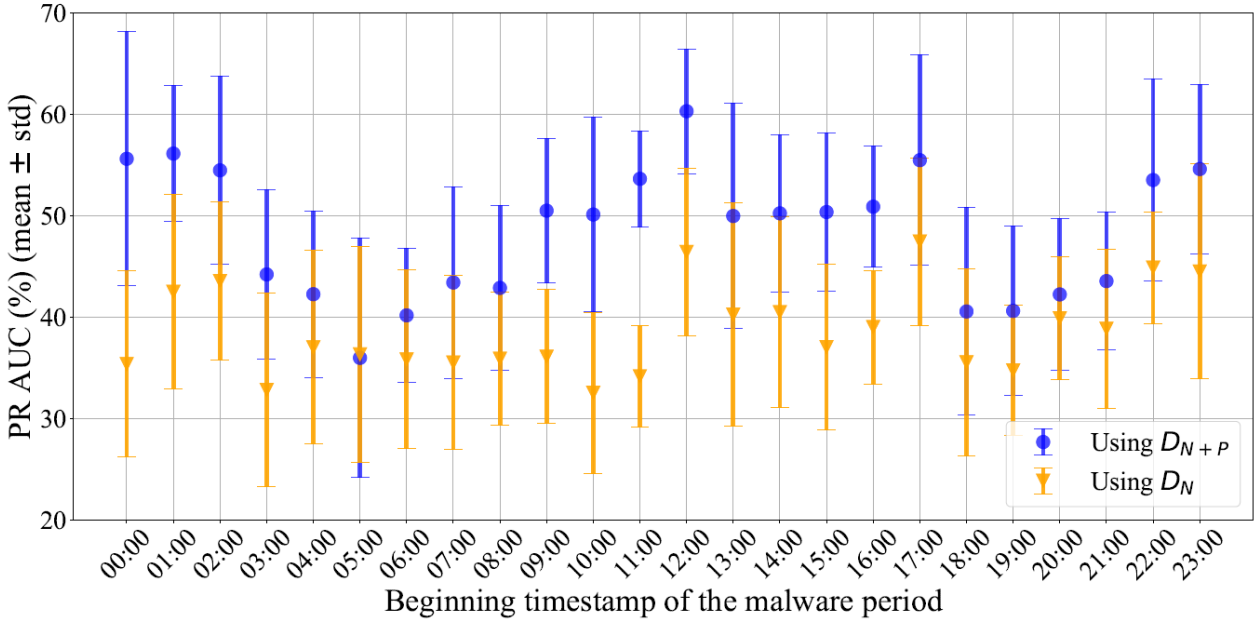
Aggregate the metrics over 10 trials

Aggregate the results over 24 injection of current malware

Aggregate the results across all malware families

Results (1/4)

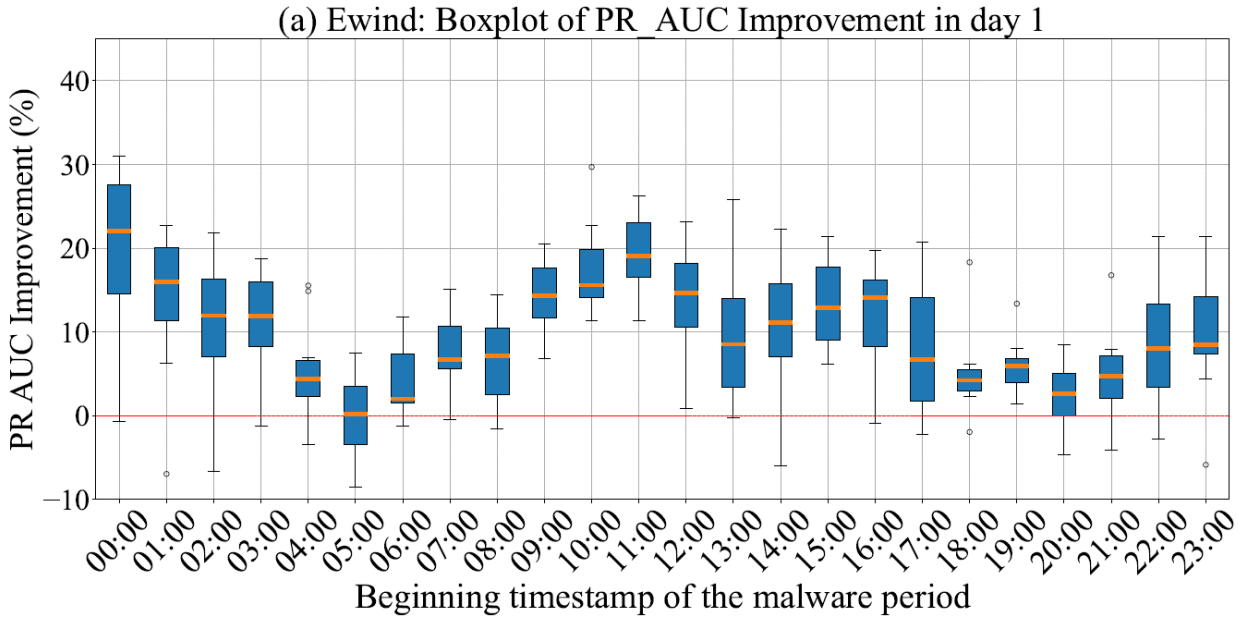
(a) Comparison of PR AUC between using D_{N+P} and D_N



Note: PR AUC $_{\text{Random guesser}}$ = # positive samples / # all samples (= 8.3% in this work)

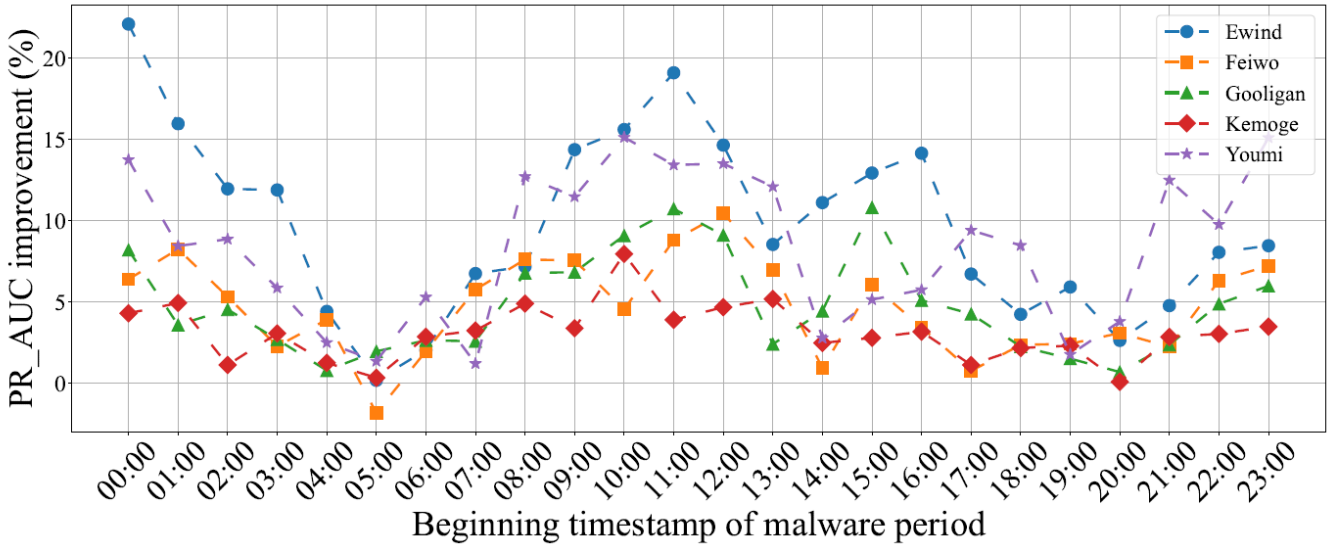
Results (2/4)

(b) PR AUC Improvement (= PR AUC using D_{N+P} - PR AUC using D_N)



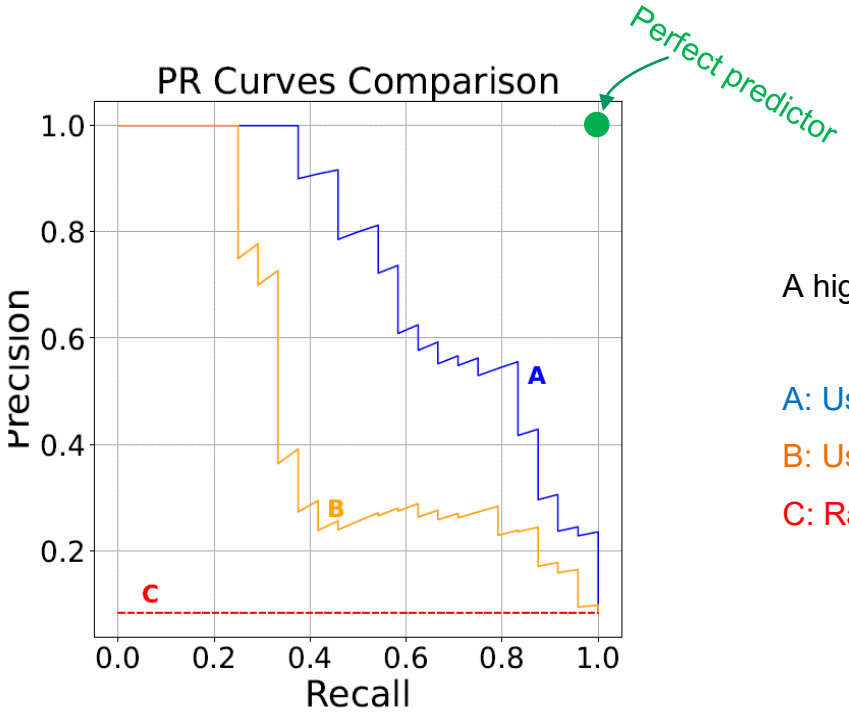
Results (3/4)

(c) PR AUC Improvement (mean values) across 5 malware families



Results (4/4)

(d) PR curve comparison at a specific timestamp (00h00, day 1)



A higher PR AUC indicates better performance.

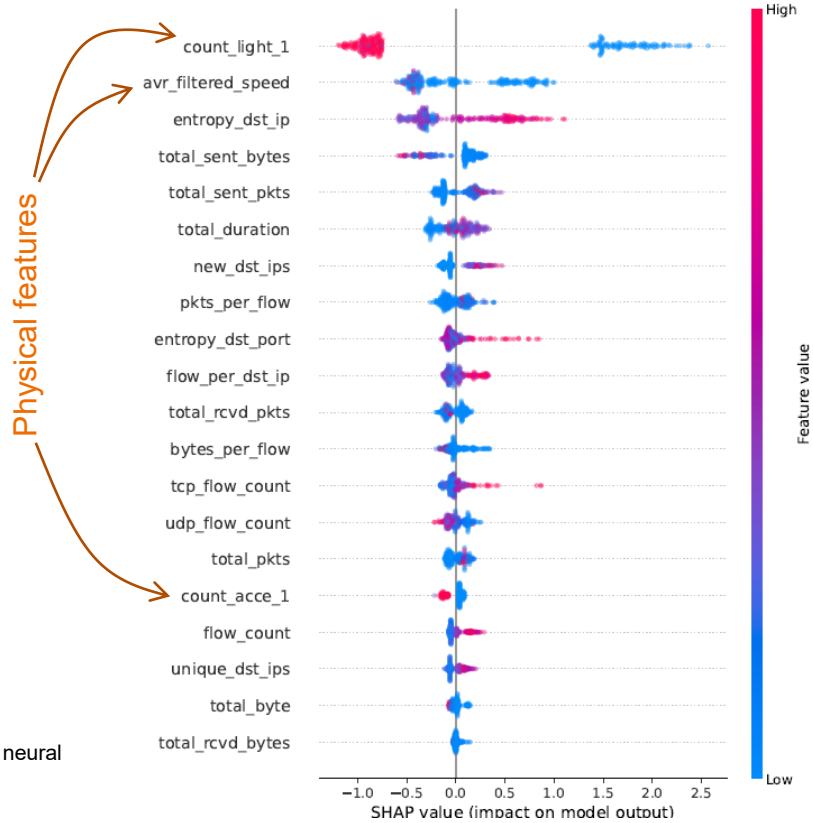
A: Using D_{N+P}	PR AUC = 0.7393
B: Using D_N	PR AUC = 0.4767
C: Random guesser	PR AUC = 0.0830

Explaination by SHAP

- The **SHAP** (SHapley Additive exPlanations) methodology[3]
  - A game-theoretic approach
  - Explain the output of machine learning models
  - Assign importance values to individual variables (features)

⇒ Specific physical signals are critical (ambient light, user speed)

⇒ The relevance of physical data in the decision-making of the IDS algorithm



[3] S. M. Lundberg and S.-I. Lee, “A unified approach to interpreting model predictions,” Advances in neural information processing systems, vol. 30, 2017.

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Conclusion

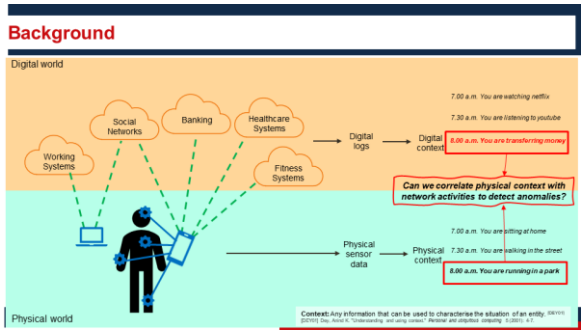
Our contributions

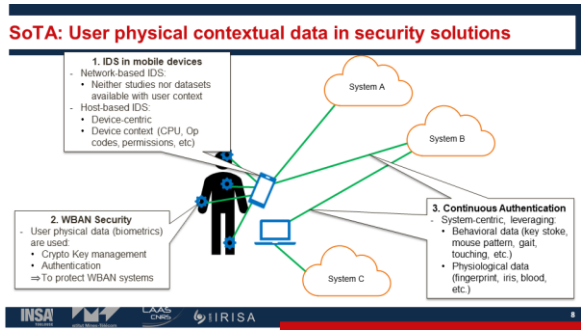
- **A new dataset** combining network traffic and physical sensor data collected from a real person's daily activities
- **A framework** leveraging user physical context data in network intrusion detection systems
- **An experimental validation** of the hypothesis that physical contextual information enhances NIDS performance

Ongoing work

- A **large-scale dataset collection** campaign at IMT Atlantique
- Unsupervised Learning methods; Multi-model Validation

Thank you!


Background
Digital world
Social Networks
Banking
Healthcare Systems
Working Systems
Fitness Systems
Digital logs
Digital context
7.00 a.m. You are watching netflix
7.30 a.m. You are listening to youtube
8.00 a.m. You are transferring money
Can we correlate physical context with network activities to detect anomalies?
Physical sensor data
Physical context
7.00 a.m. You are sitting at home
7.30 a.m. You are walking in the street
8.00 a.m. You are running in a park
Physical world
Context: Any information that can be used to characterise the situation of an entity.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• Device context (CPU, Op codes, permissions, etc)
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- User physical data (biometrics) are used:
• Crypto Key management
• Authentication
⇒To protect WBAN systems
3. Continuous Authentication
- System-centric, leveraging:
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• Physiological data (fingerprint, iris, blood, etc.)
System A
System B
System C
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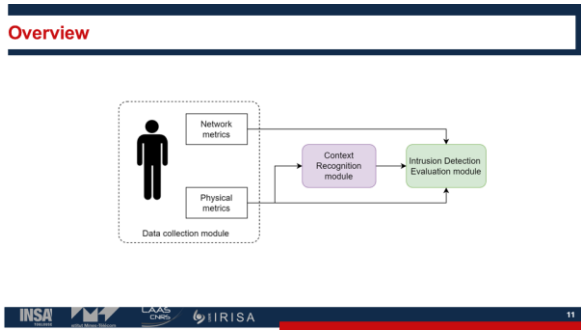
8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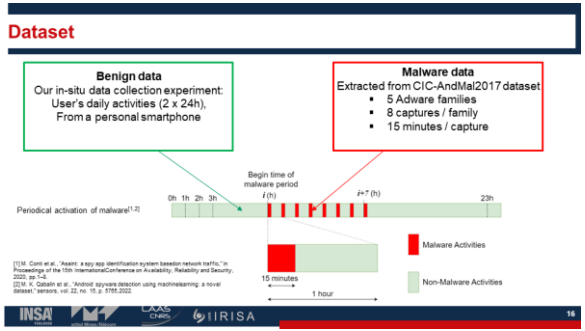
IRISA
11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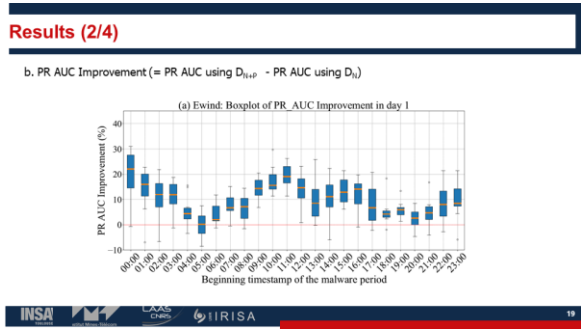
User's daily activities (2 x 24h),
From a personal smartphone
Malware data
Extracted from CIC-AndMal2017 dataset
5 Adware families
8 captures / family
15 minutes / capture
Begin time of malware period
i (h)
i+7 (h)
0h 1h 2h 3h
23h
Periodical activation of malware[1,2]
Malware Activities
Non-Malware Activities
15 minutes
1 hour
IRISA
16


Results (2/4)
b. PR AUC Improvement (= PR AUC using D_N+P - PR AUC using D_N)
(a) Ewind: Boxplot of PR_AUC Improvement in day 1
PR AUC Improvement (%)
Beginning timestamp of the malware period
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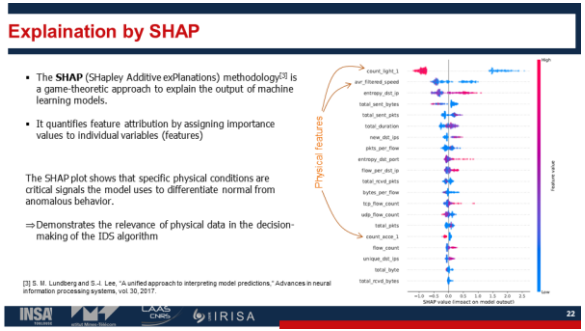
19


Explaination by SHAP
The SHAP (SHapley Additive exPlanations) methodology[3] is a game-theoretic approach to explain the output of machine learning models.
It quantifies feature attribution by assigning importance values to individual variables (features)
The SHAP plot shows that specific physical conditions are critical signals the model uses to differentiate normal from anomalous behavior.
⇒Demonstrates the relevance of physical data in the decision-making of the IDS algorithm
Physical features
[3] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," Advances in neural information processing systems, vol. 30, 2017.
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