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FEDERATED LEARNING × SECURITY IN NETWORK MANAGEMENT

YANN BUSNEL
IMT NORD EUROPE

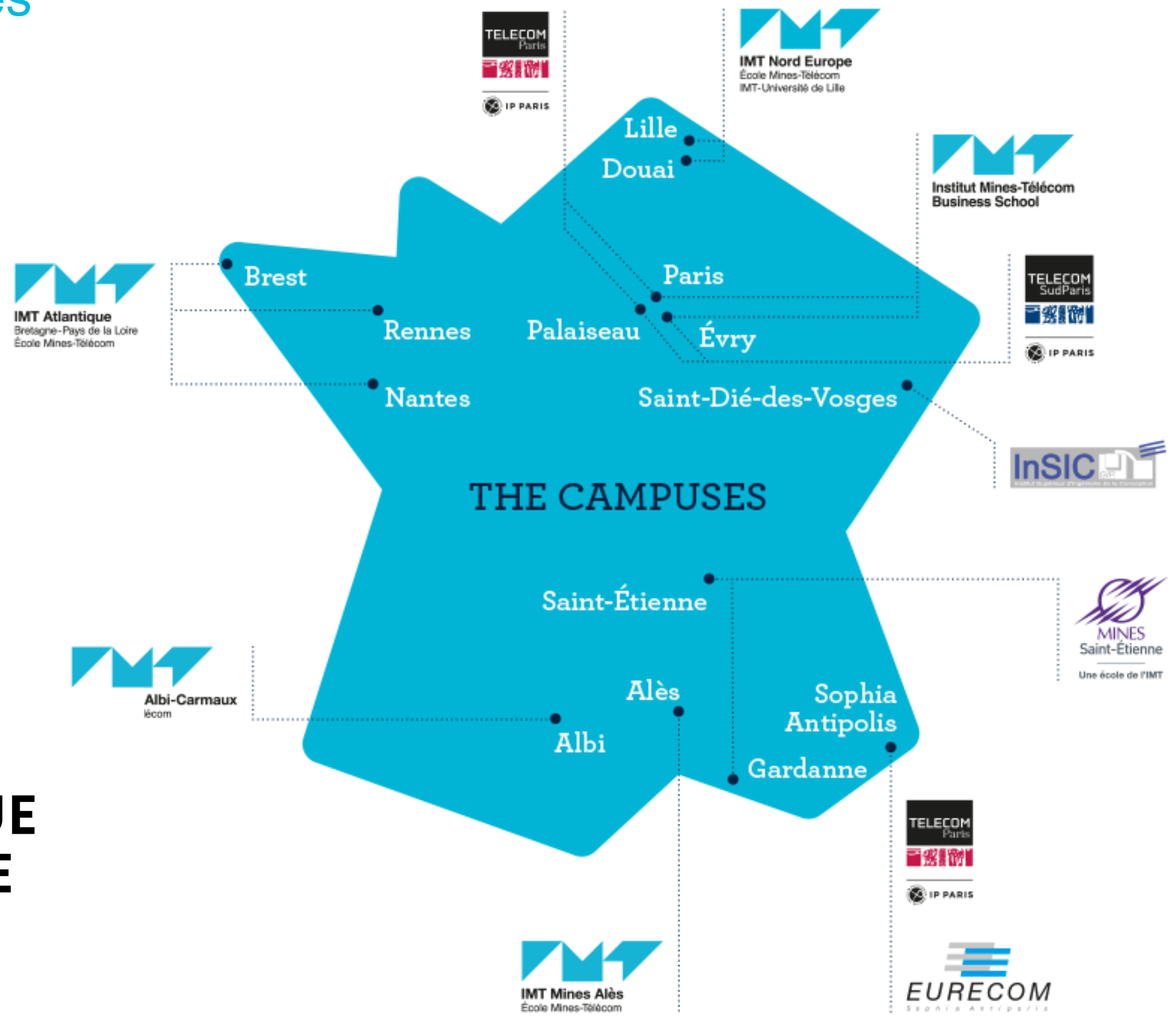
LEO LAVAUR
IMT ATLANTIQUE

JULY 23RD, 2024 — IEEE ICDCS — JERSEY CITY, USA

WHAT IS IMT?

8 Technological Universities
2 Subsidiaries

Institut Mines-Télécom



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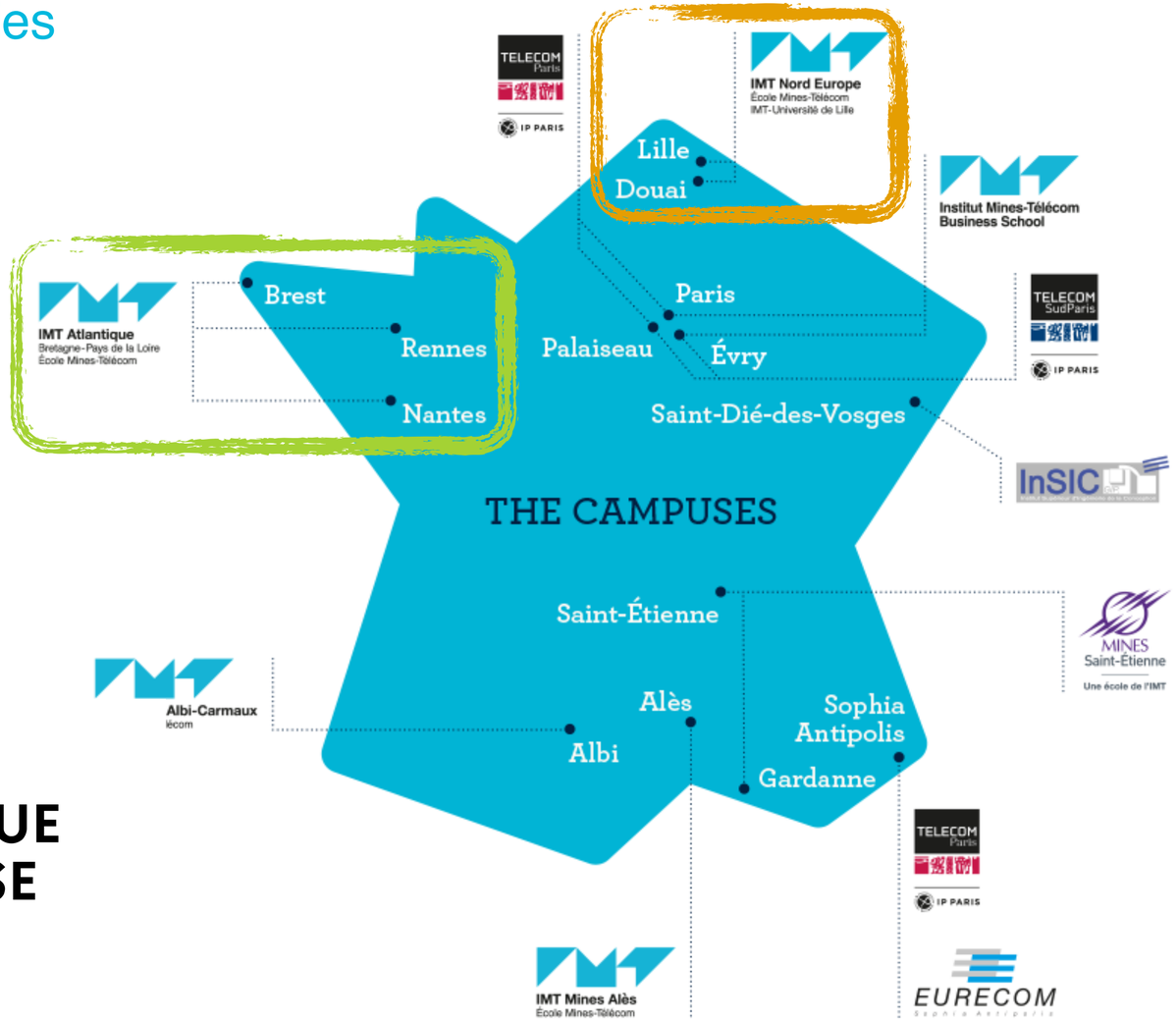

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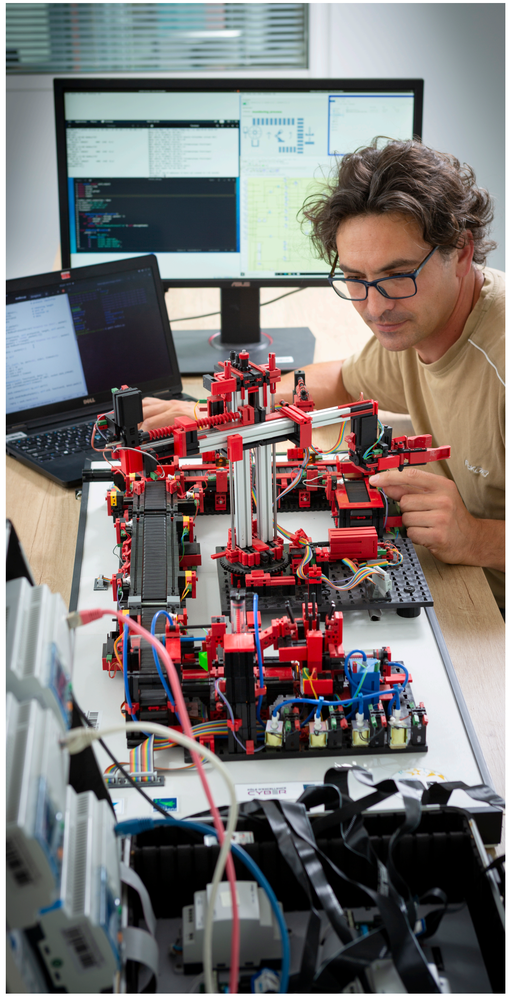
RESEARCH PLATFORMS: CENCYBLE BUILDING AND REALISTIC TESTBEDS



LET'S TALK ABOUT FEDERATION

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ALL START FROM CROWDSOURCING

- **« Large group of dispersed participants contributing or producing goods or services […] for payment or as volunteers »**
  Wikipedia, 2023
- **Waze Example**

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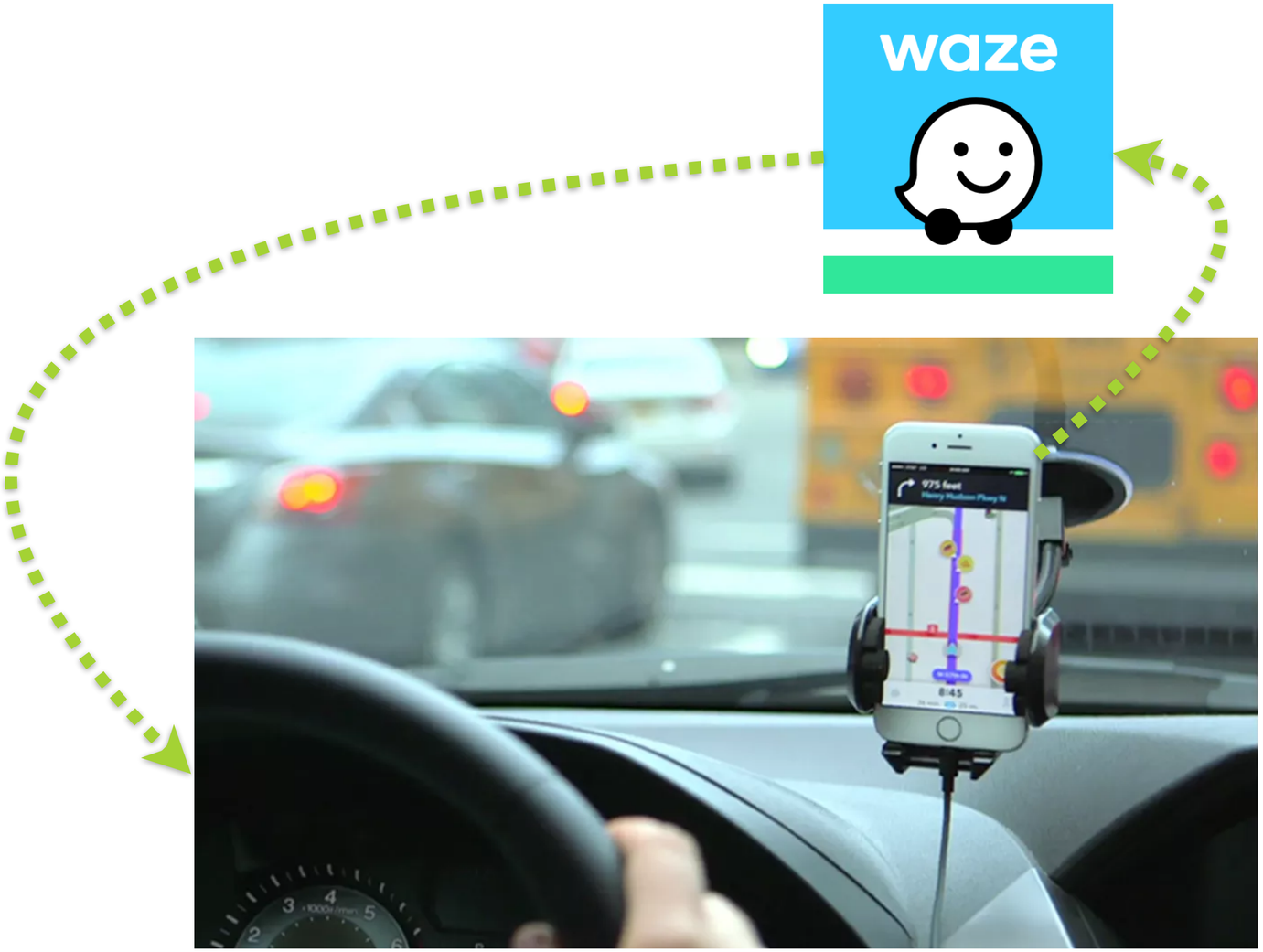

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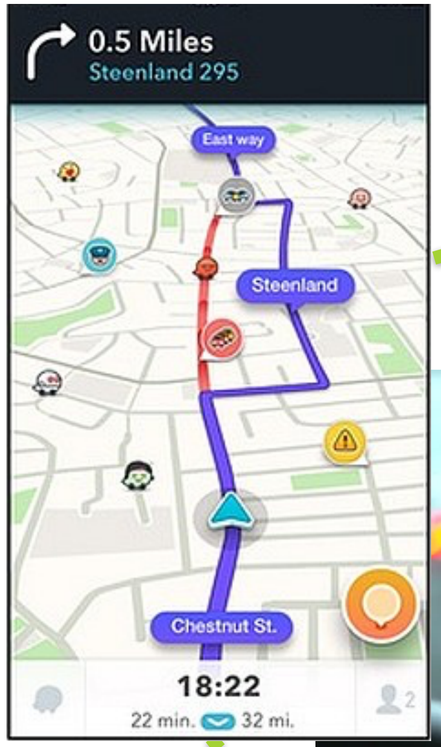

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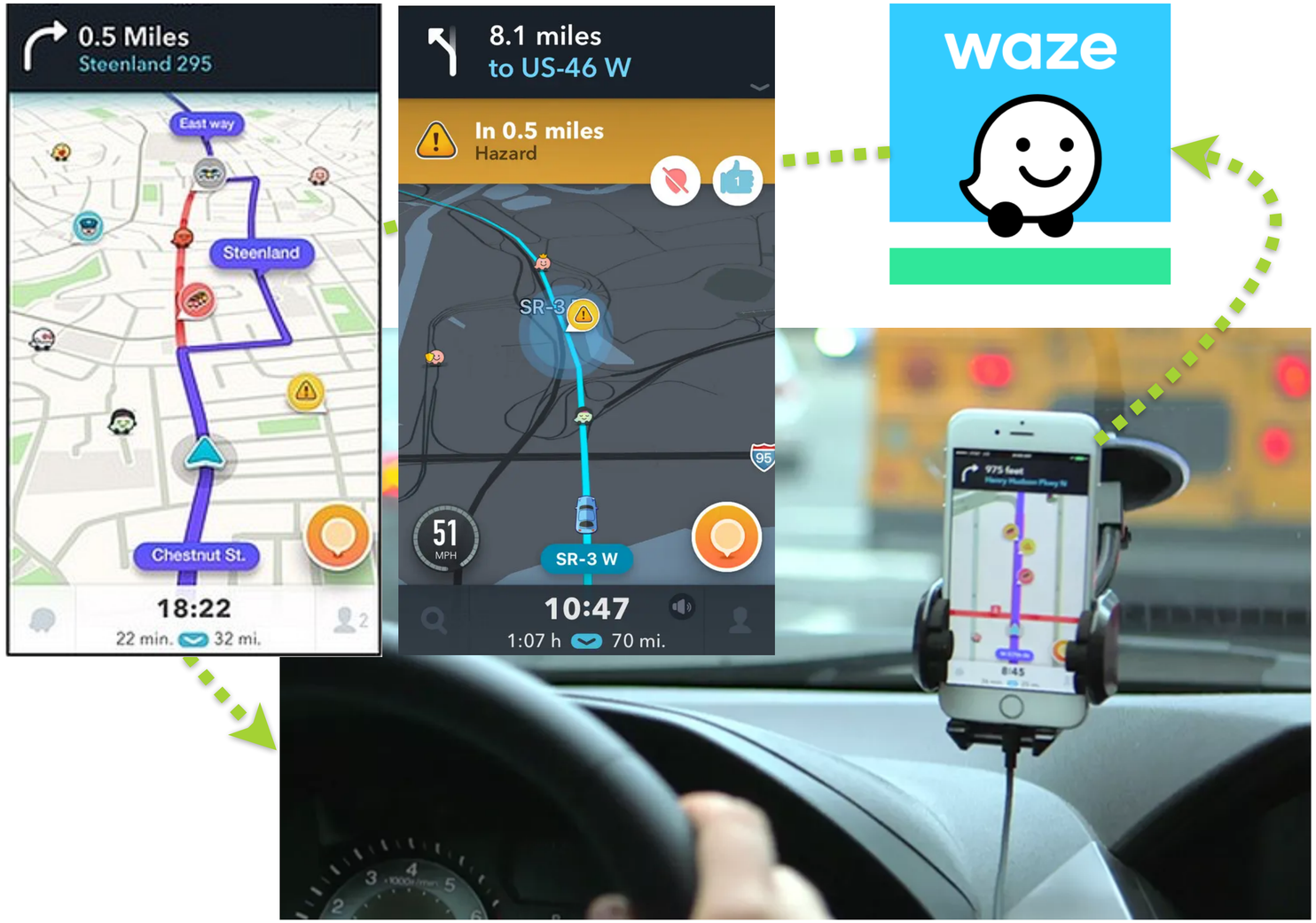
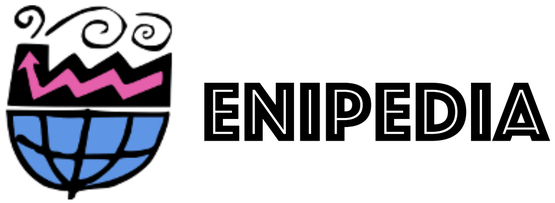


ALL START FROM CROWDSOURCING

- **Hotel or attraction reviews**
- **Collaborative journalism**
- **Unused room business**
- **Energy industry data**
- ***etc.***



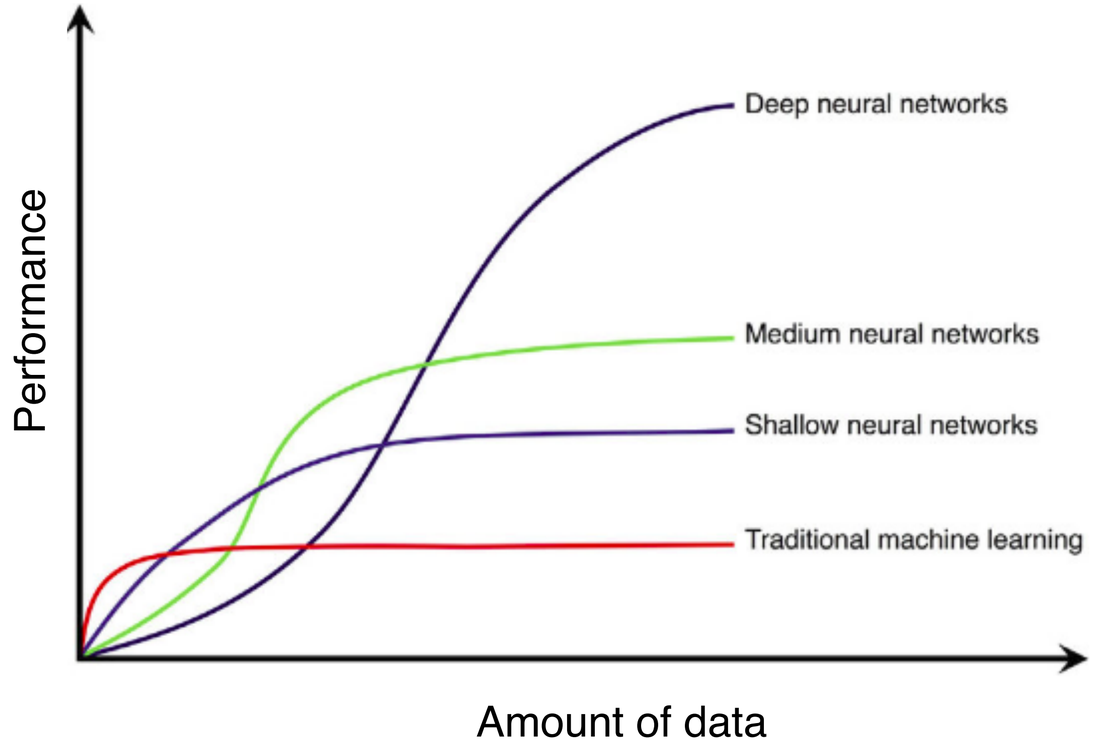
INDUSTRIALIZING CROWDSOURCING

amazon mechanical turk

CloudResearch® connect™

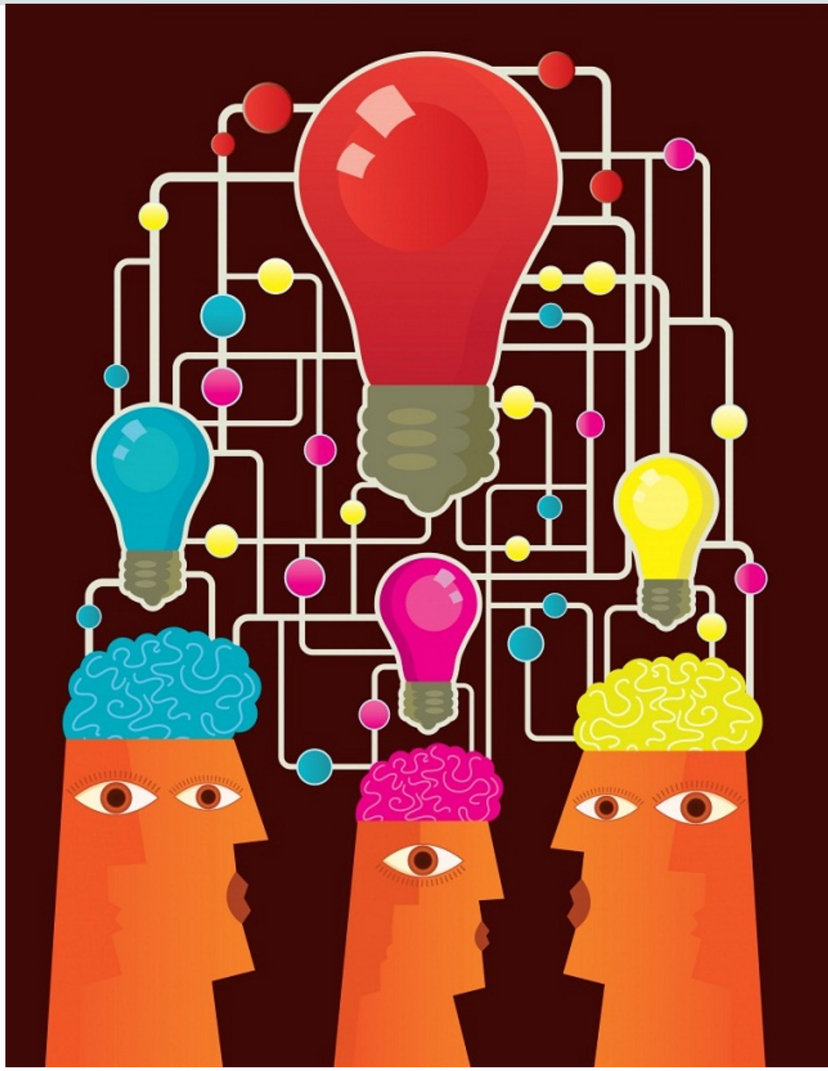
APPLICATION TO MACHINE LEARNING

- **Performance improve with more data**
  - Increases accuracy
  - Scales to larger input data sizes
- **If computational complexity outpaces the main memory**
  - Not scale well due to memory restrictions

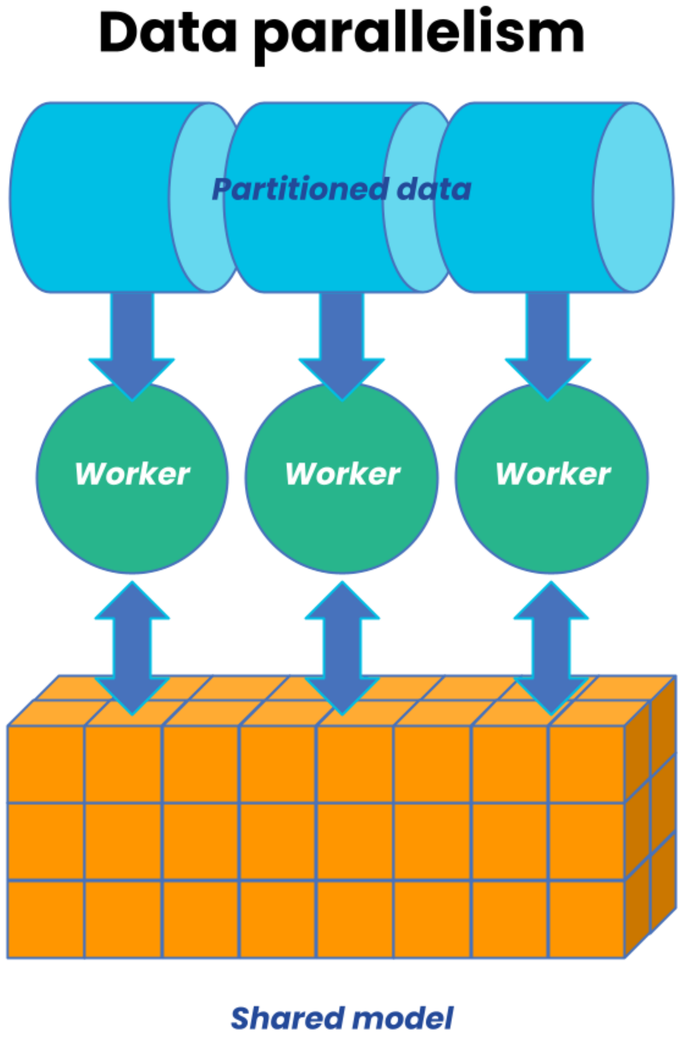


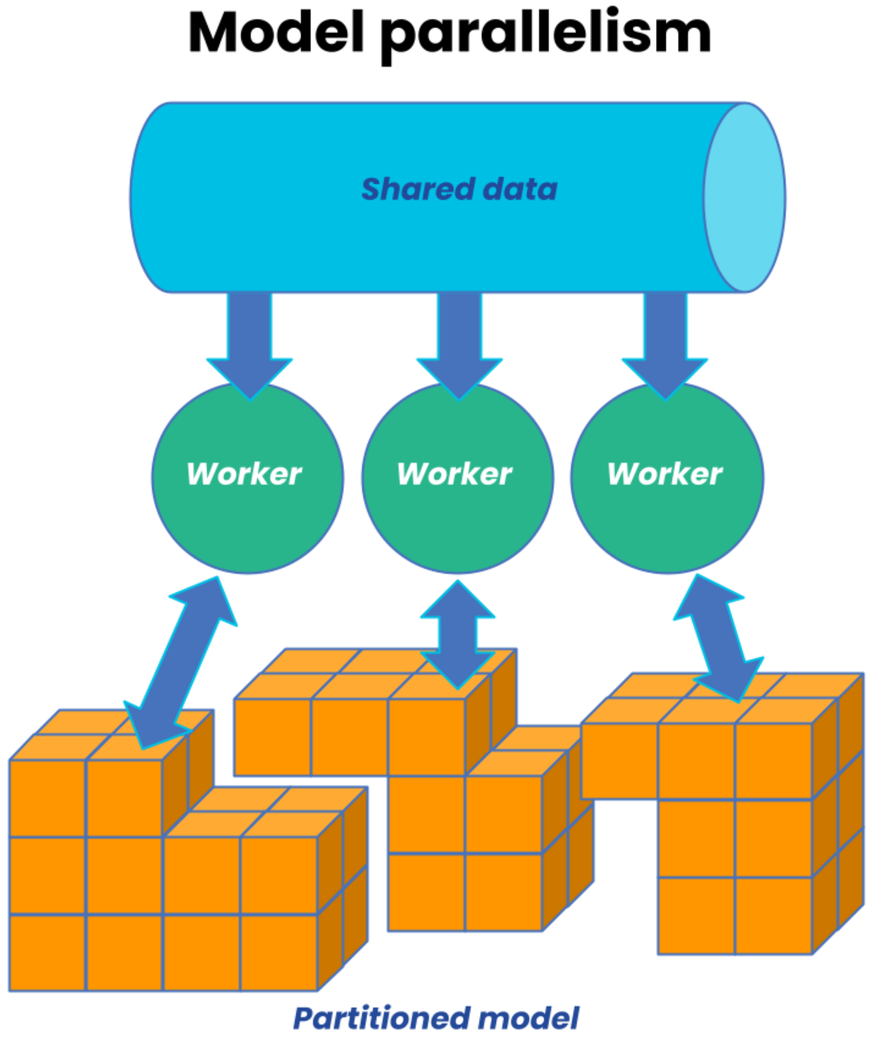
INTRODUCTION OF DISTRIBUTED MACHINE LEARNING

- **Handle large data sets**
- **Develop efficient and scalable algorithms**
- **Ability to allocate learning processes onto several workstations**
  - Enable faster learning algorithms
- **Often used in healthcare or advertising**



CONCEPT OF DISTRIBUTED MACHINE LEARNING





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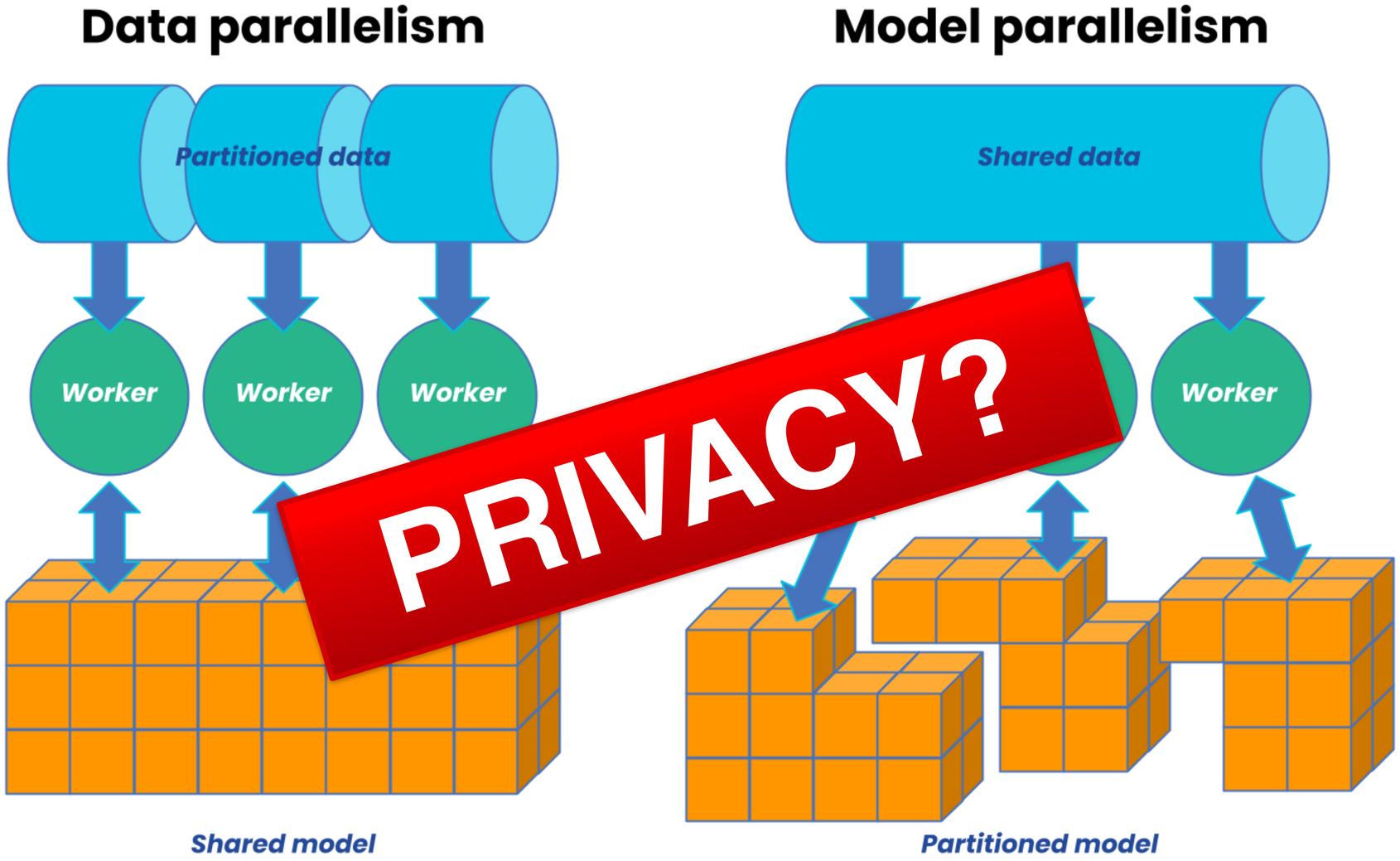
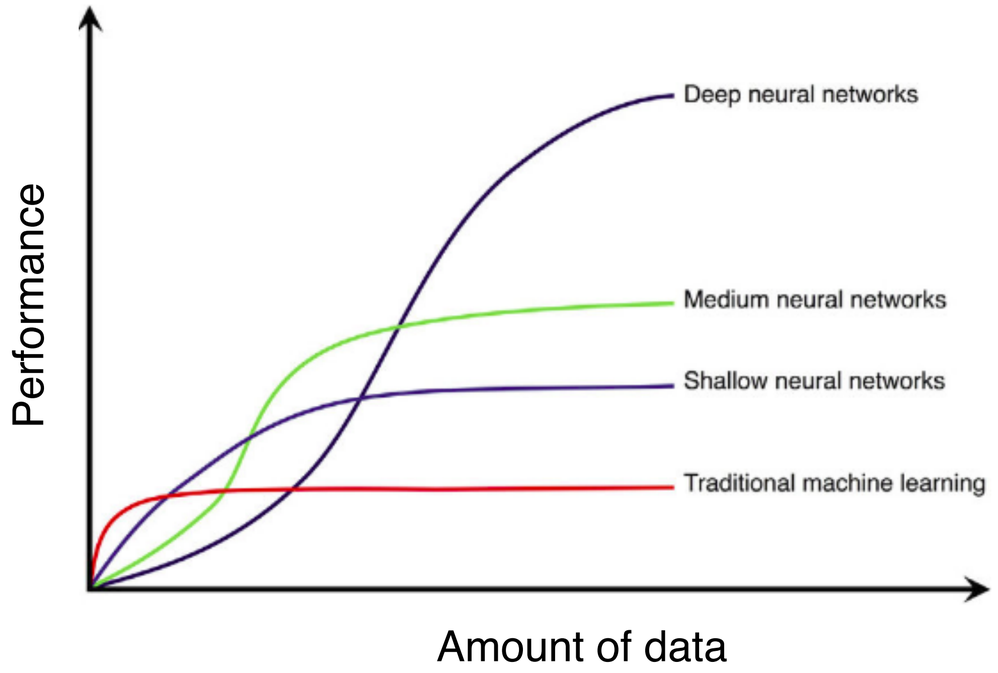


MOTIVATION FOR FEDERATED LEARNING

- **Performance improve with more data**
- **Models can be meaningfully combined**
- **Nodes can *trains* model, not only predict**
- **Need to preserved privacy at all costs**
  - Interest of HIPAA and GDPR regulations



FEDERATED LEARNING IN A NUTSHELL

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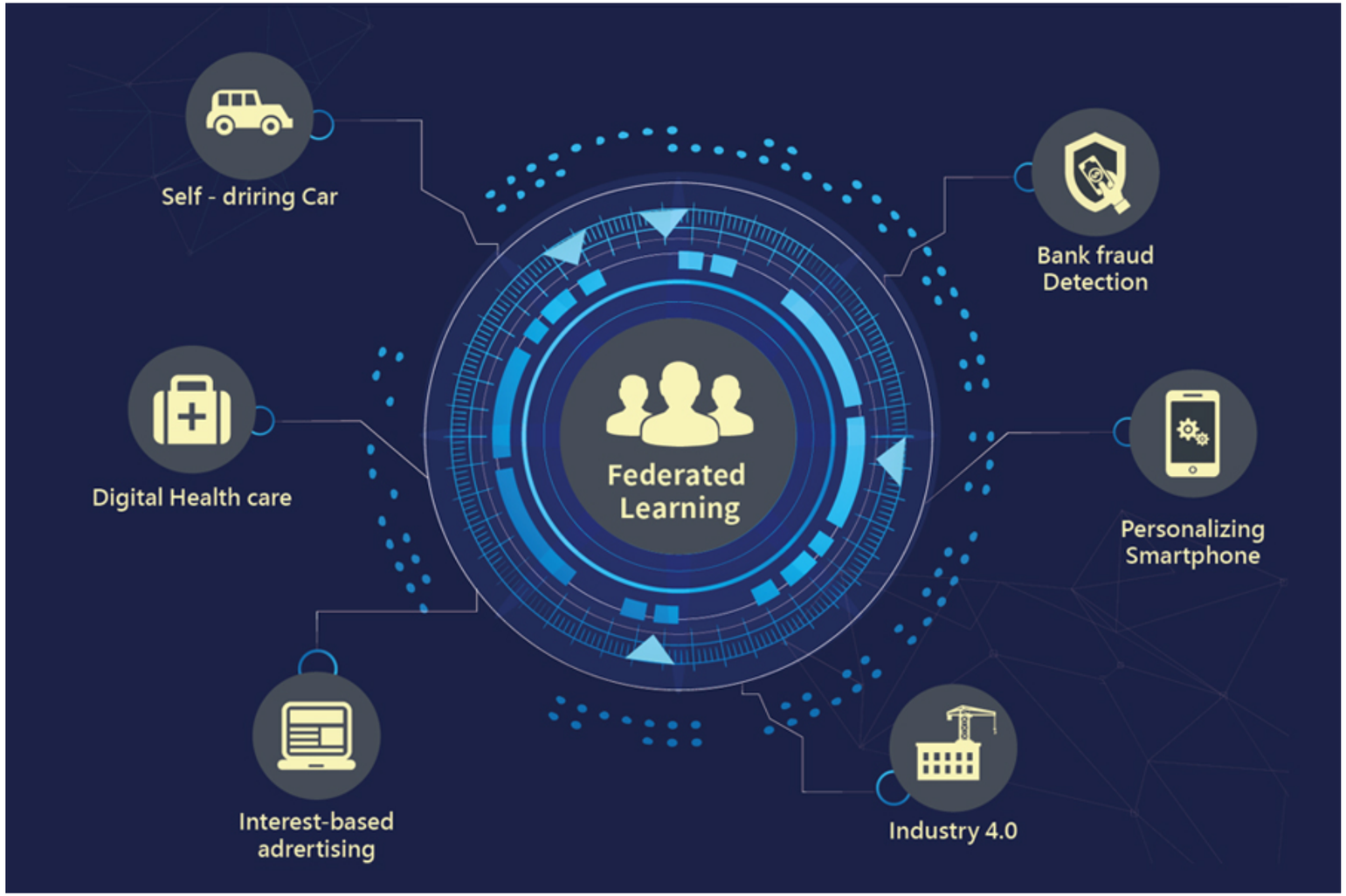
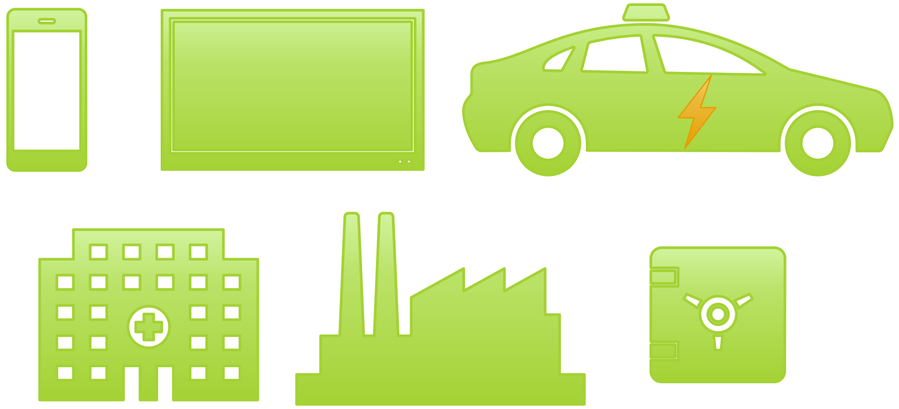
FEDERATED LEARNING (FL) APPROACH



- **Multiple participants**
  - Contributes individually
- **All sort of devices**
  - Users' interaction data
  - Enough processing power



FEDERATED LEARNING PRINCIPLE

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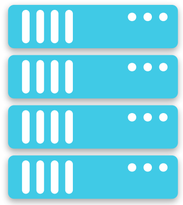

Server

FEDERATED LEARNING PRINCIPLE

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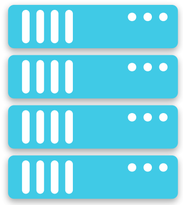

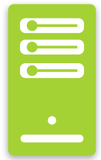

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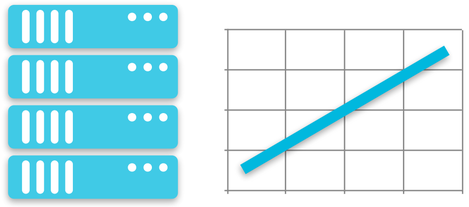

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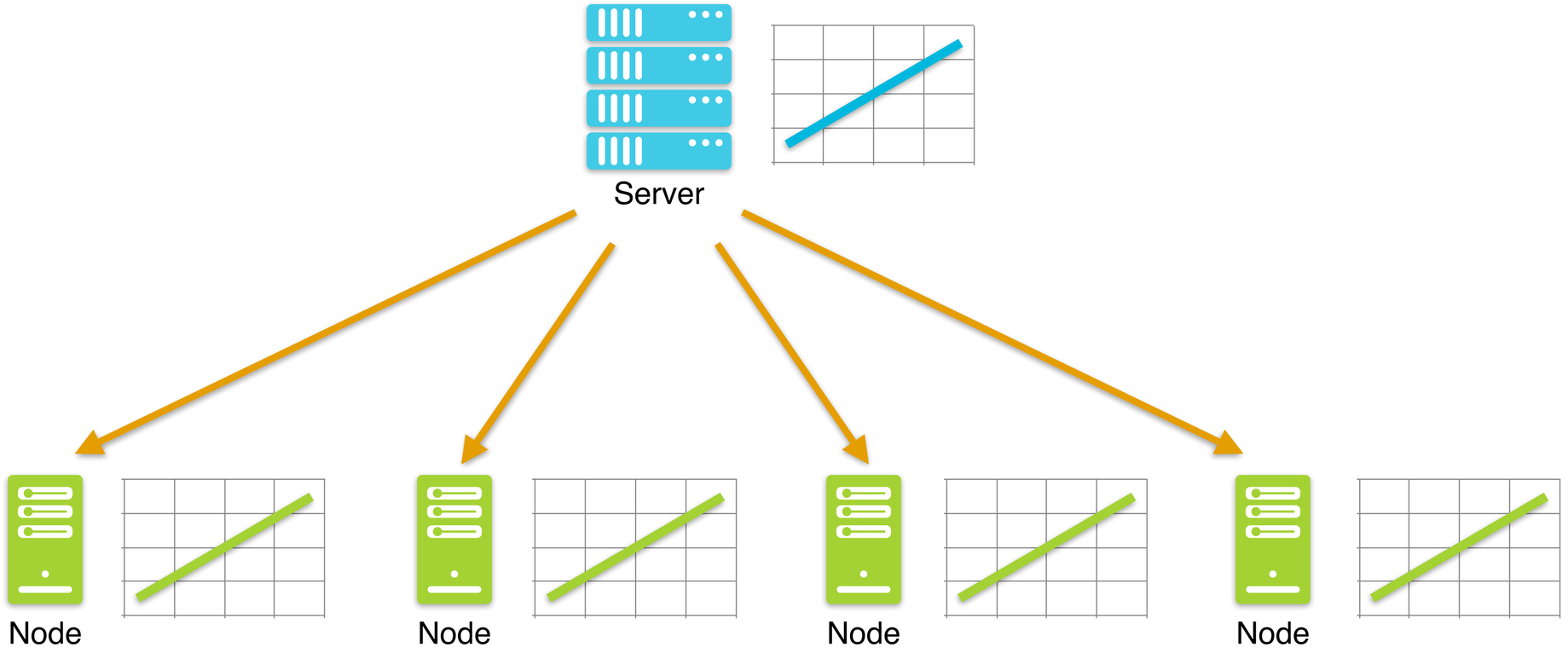

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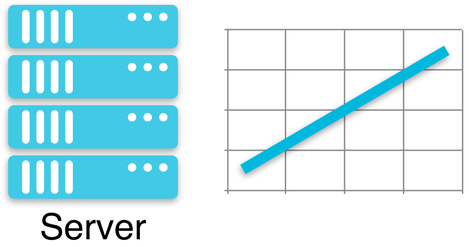

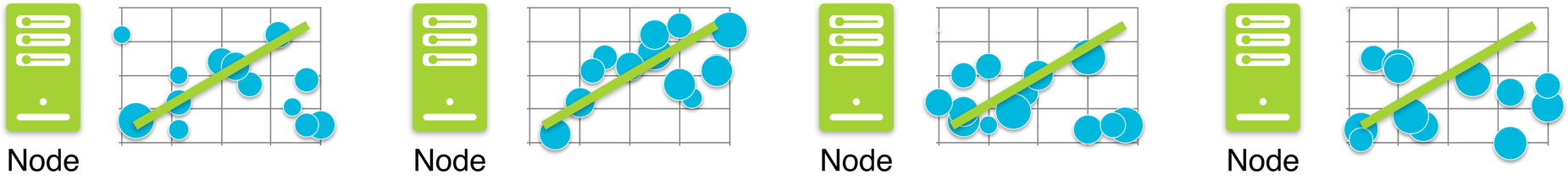

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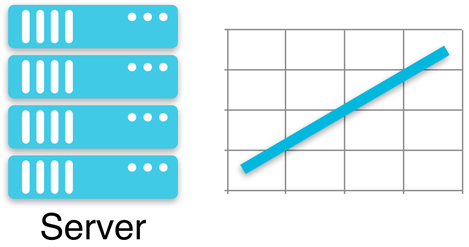

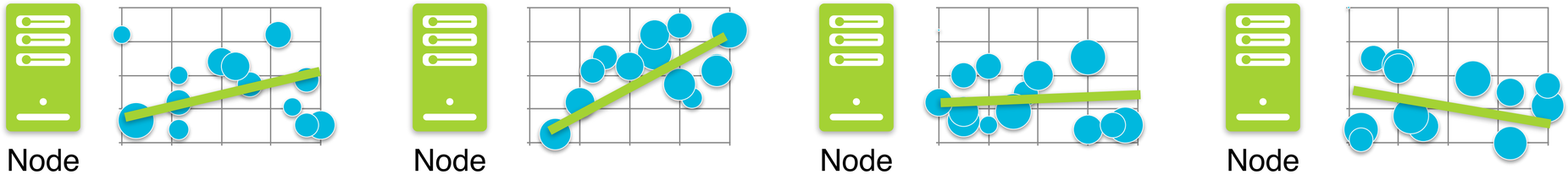

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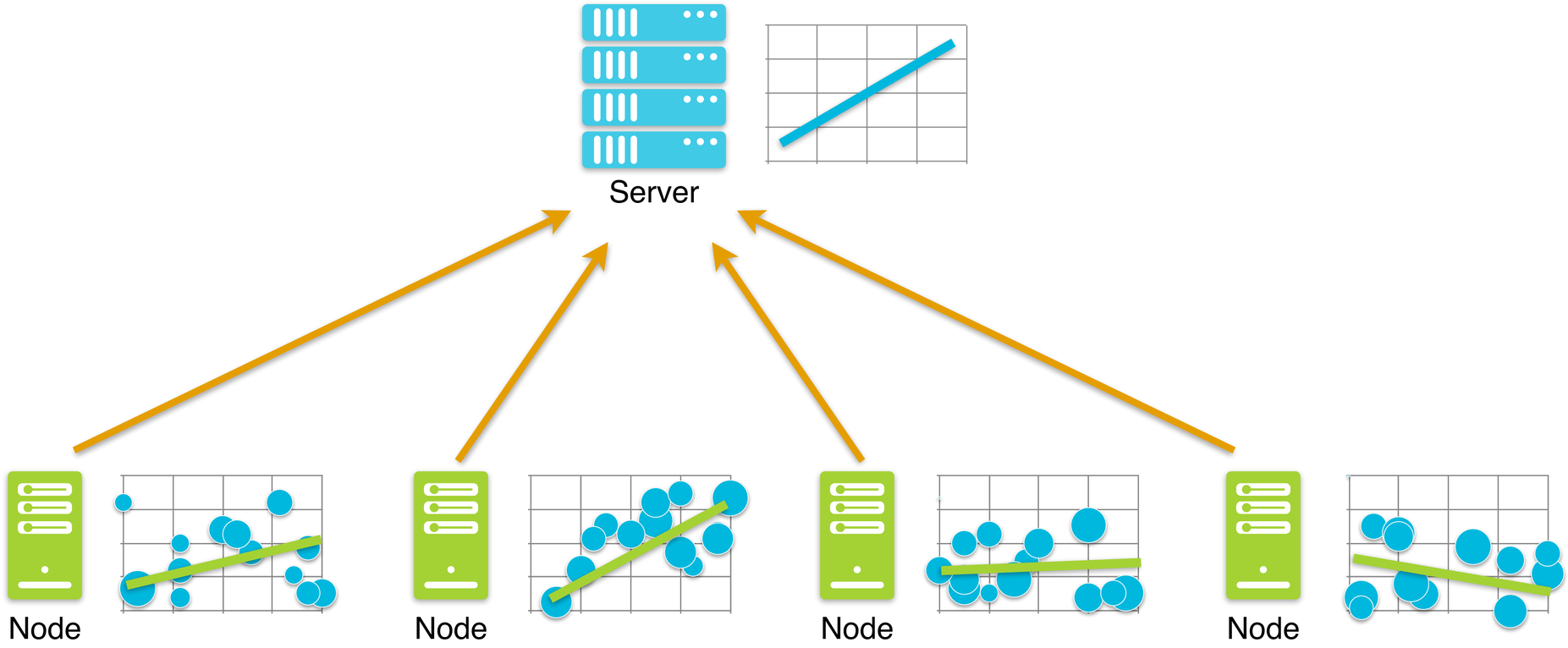

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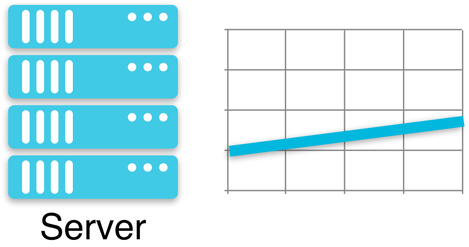

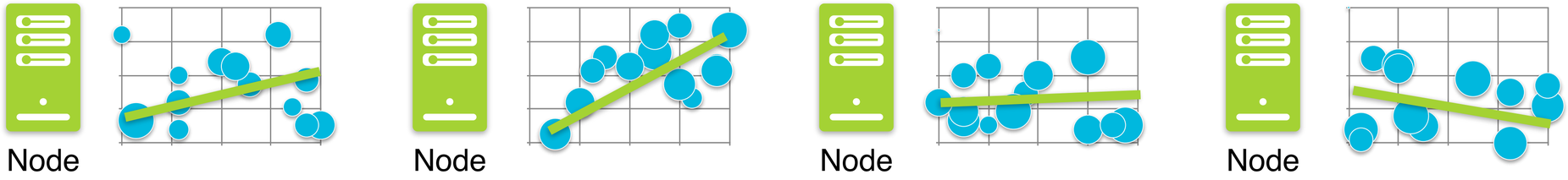

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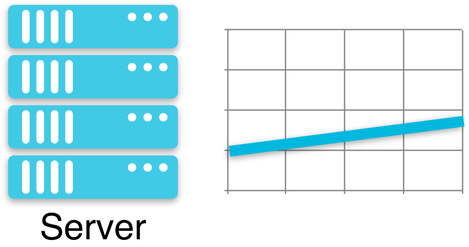
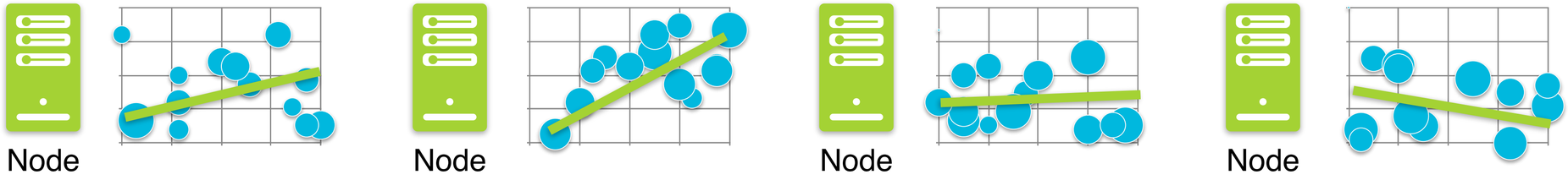
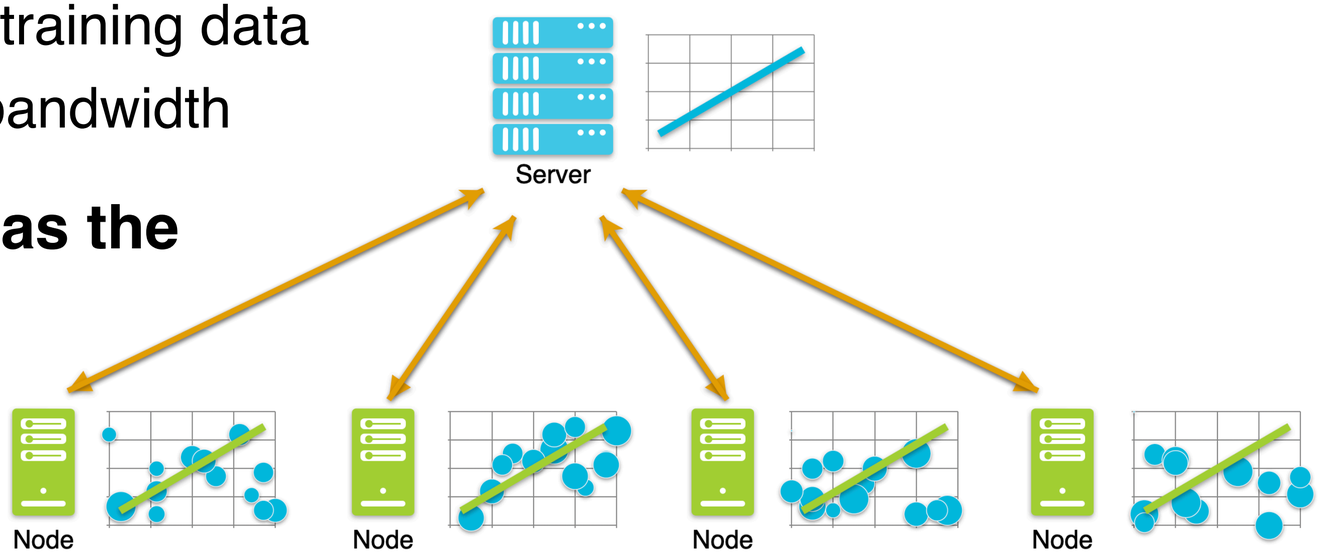




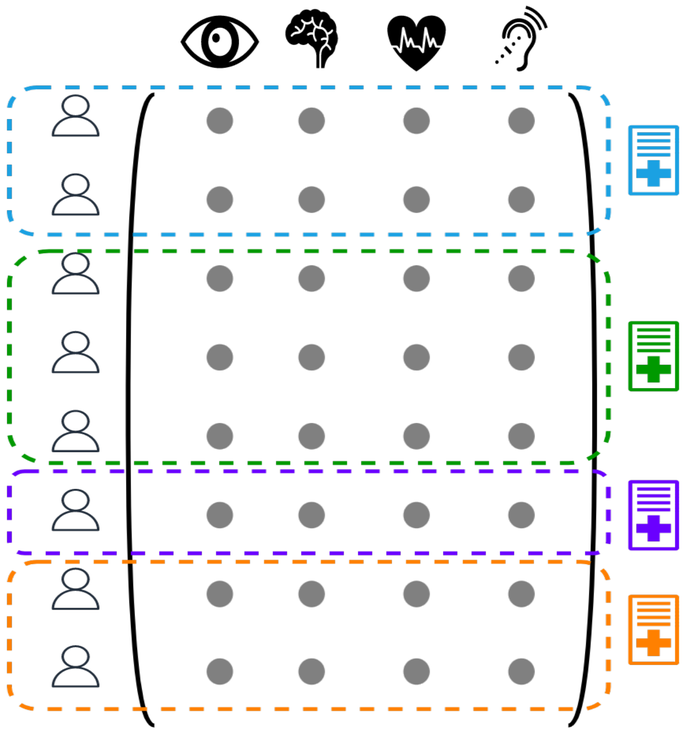
- **We repeat the whole process many times**

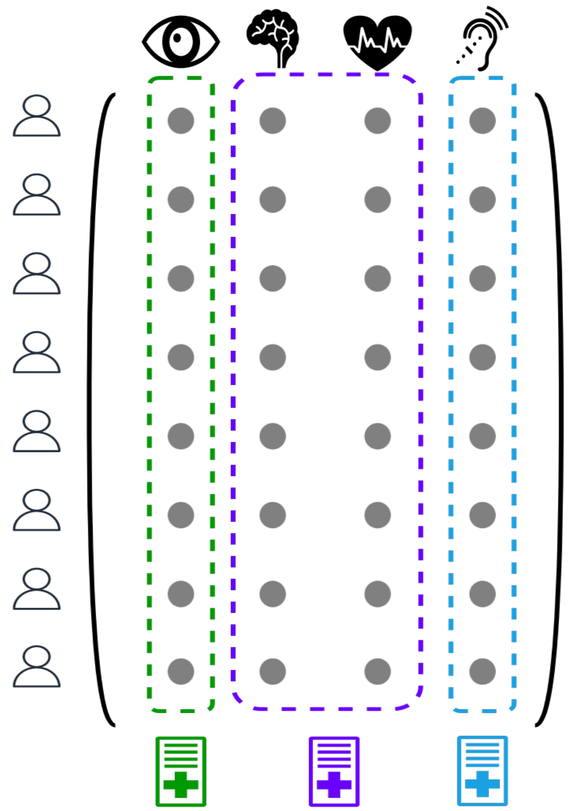
FEDERATED LEARNING PRINCIPLE

- **A network of nodes shares *models* rather than *training data* with the server**
- **We repeat the whole process many times**
- **The server has now a model that captures the pattern in the training data on all the nodes**
  - But, at no point, the nodes share their training data
  - That increases privacy and saves on bandwidth
- **Ideally, the final model is as good as the centralized solution**
  - At least, better than what each party can learn on its own



DIFFERENT TYPE OF FEDERATED LEARNING

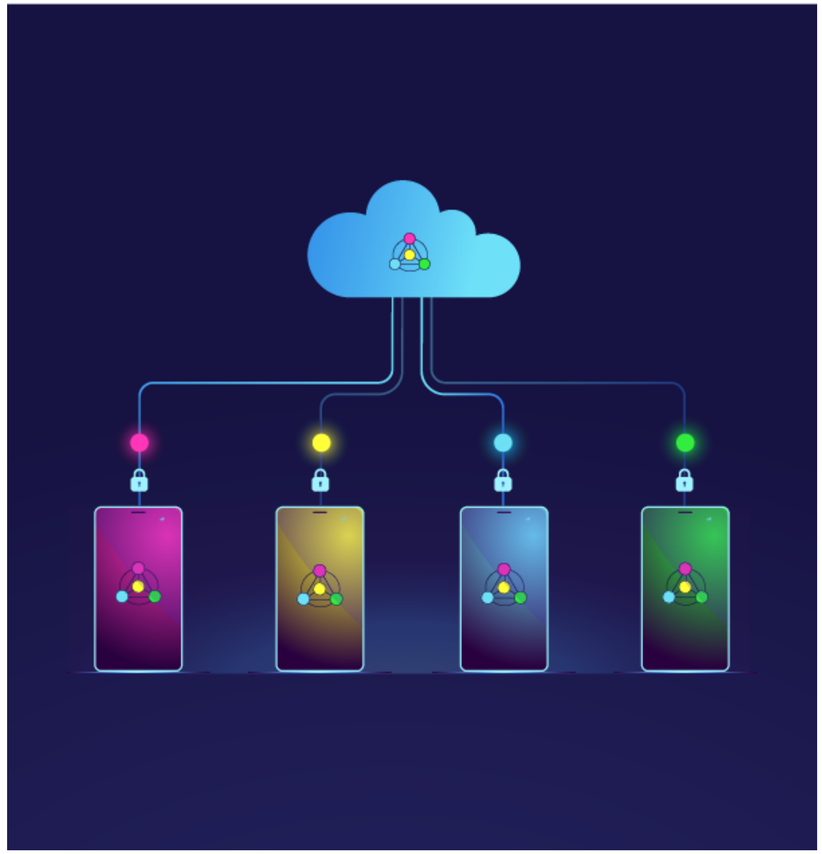




- **Horizontal Federated Learning**
  - Clients share the feature and labels space
  - Differ in the sample space
- **Vertical Federated Learning**
  - Clients share the sample space
  - But neither the feature nor label space

FEDERATED LEARNING CAN HANDLE…

- **Non-IID data**
  - Training data on each node can be idiosyncratic
- **Unbalanced data**
  - Unequal amount of data on each node
- **Massively distributed data**
  - Can have many more devices than training exemples per node
- **Limited communication**
  - Cannot guarantee availability of nodes
- **Training and testing operated on nodes**



EXAMPLE WITH FEDAVG (FEDERATED AVERAGING)

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EXAMPLE OF FEDAVG

- **From a pool of candidates**
  - Chooses a subset of *eligible* participants
    - fully charged
    - specific hardware configurations
    - connected to a reliable and free WiFi network
    - idle
- **Not all devices participate in the federation**

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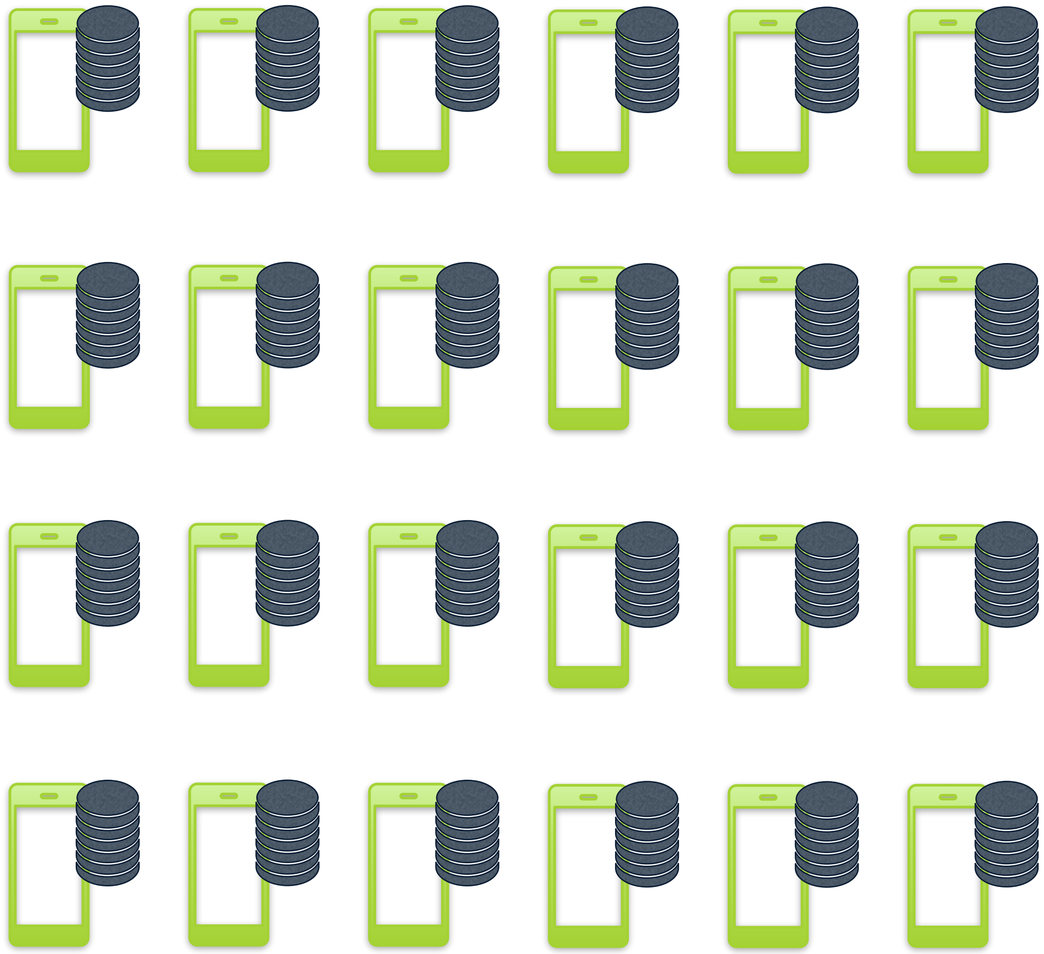

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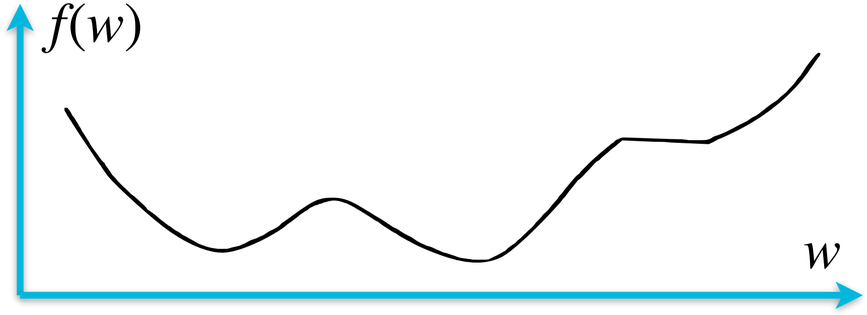
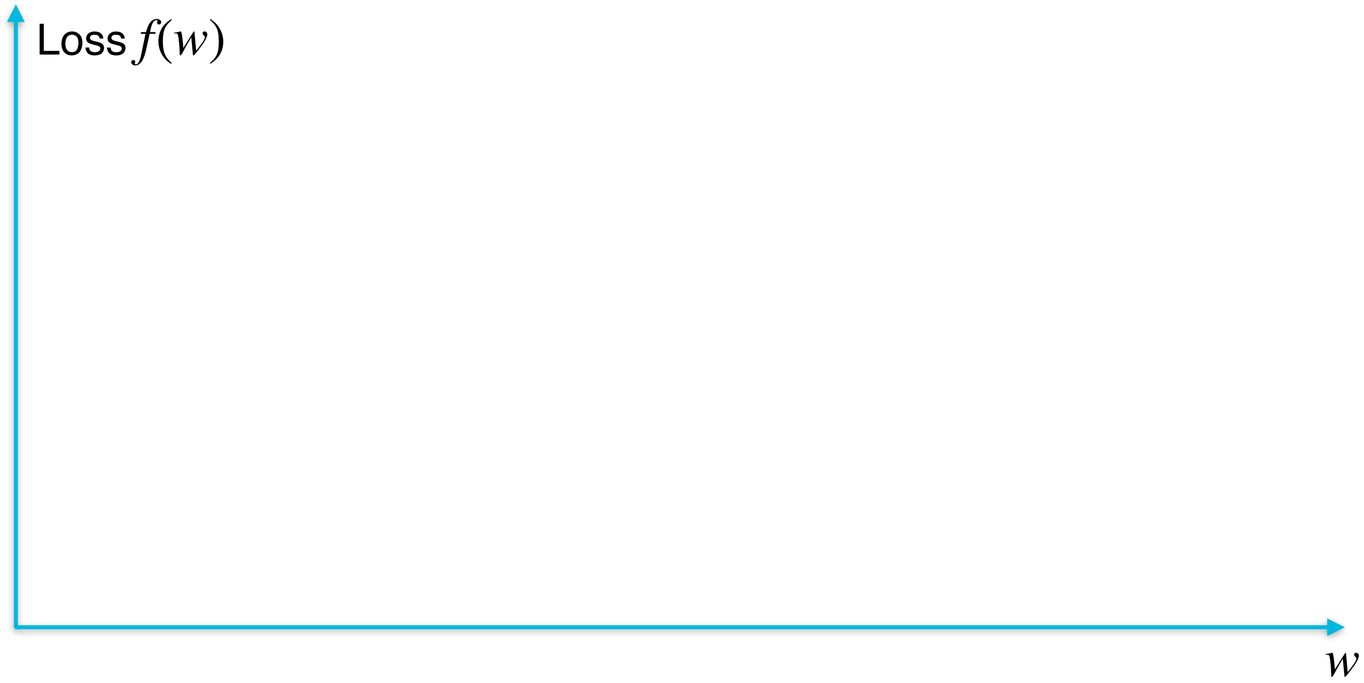
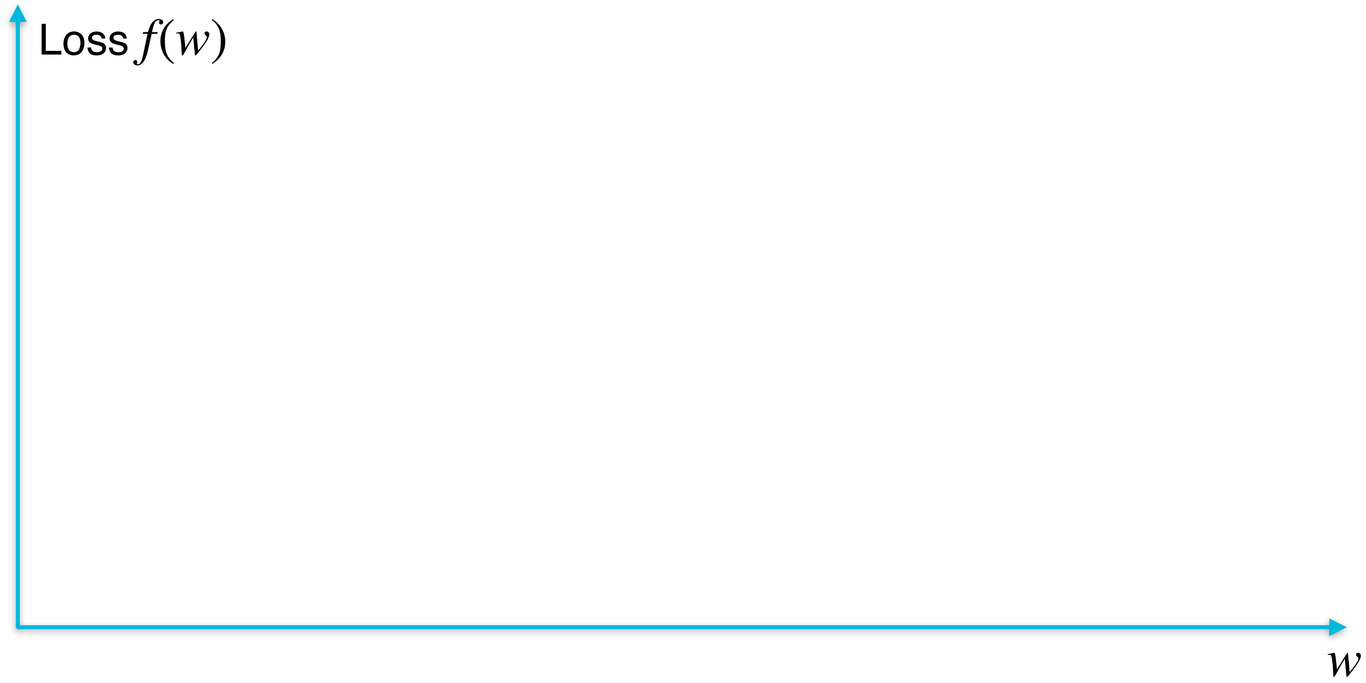
- **For a training dataset containing n samples $(x_i, y_i)_{1 \leq i \leq n}$, the training objective is**
  - $\min_{w \in \mathbb{R}^d} f(w)$ where $f(w) = \frac{1}{n} \sum_{i=1}^{n} f_i(w)$
  - with $f_i(w) = l(x_i, y_i, w)$, the loss of the prediction on example (x_i, y_i)
- **Properties**
  - Non-convex
    - Multiple local minima exist
  - No closed-form solution
    - In a typical deep learning model, w may contain millions of parameters



EXAMPLE OF FEDAVG — RECALL OF GRADIENT DESCENT



Solution: Gradient descent



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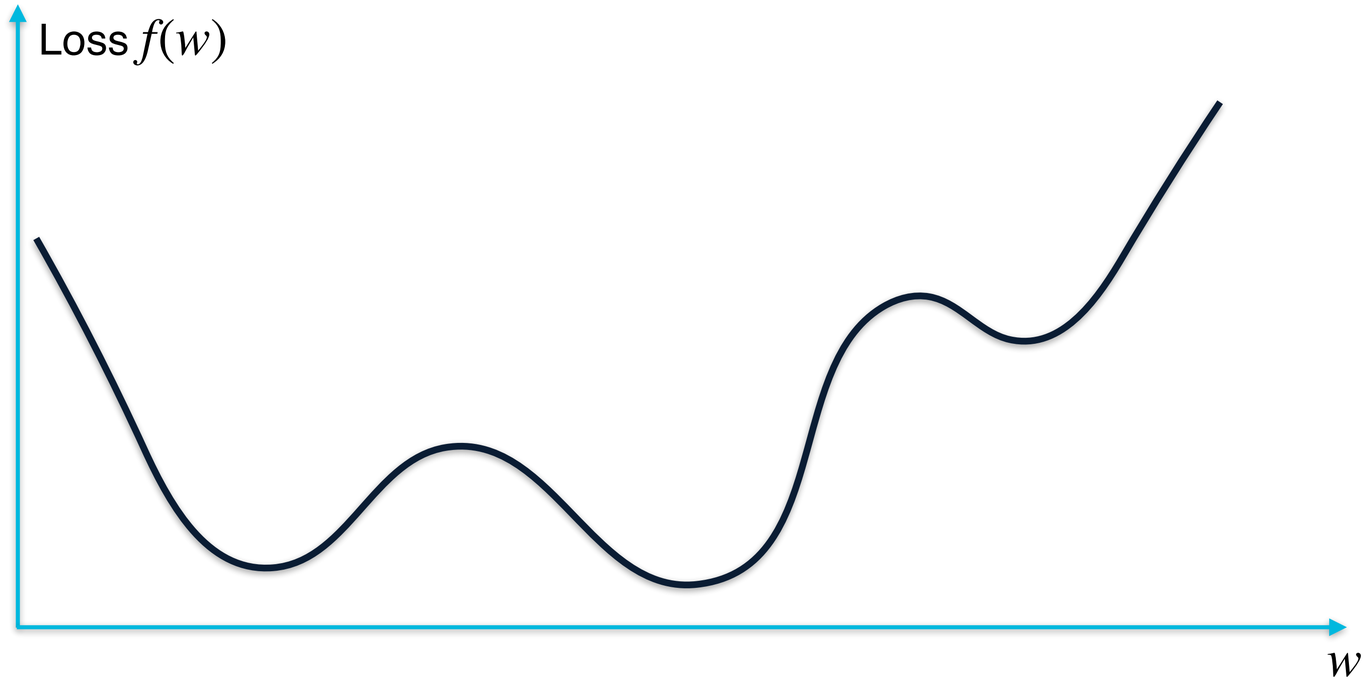

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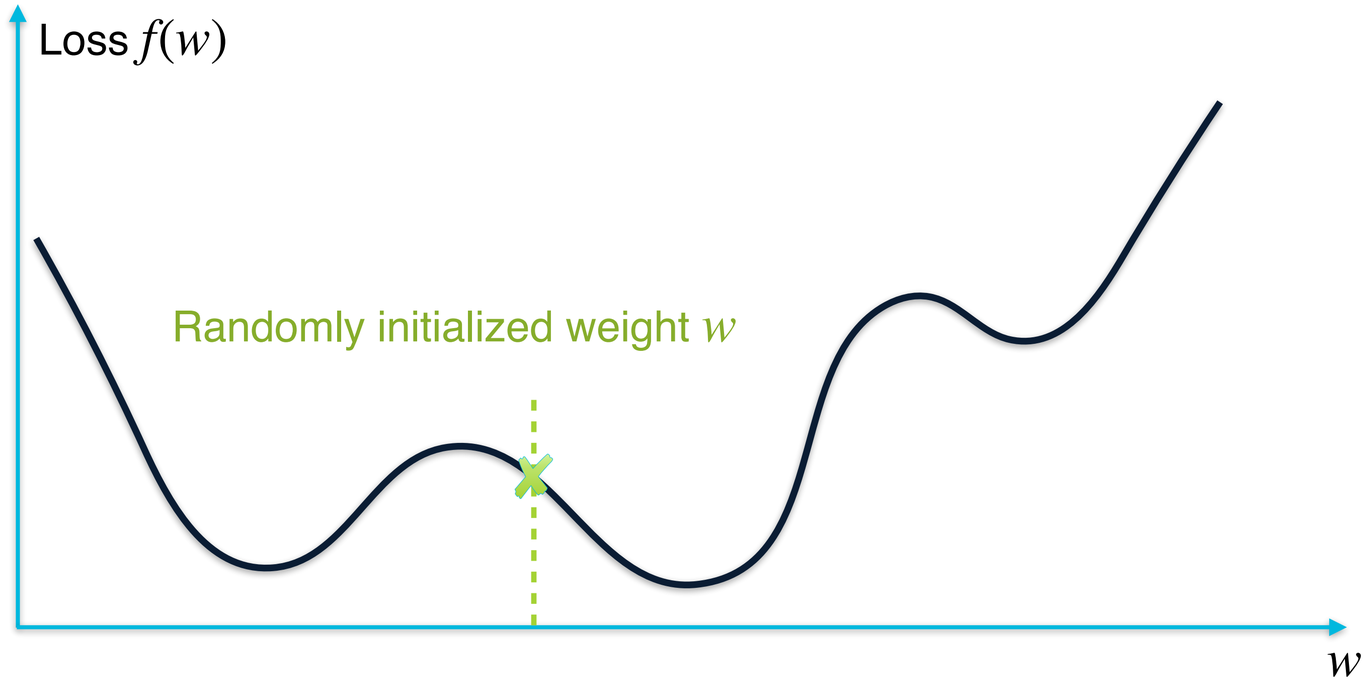

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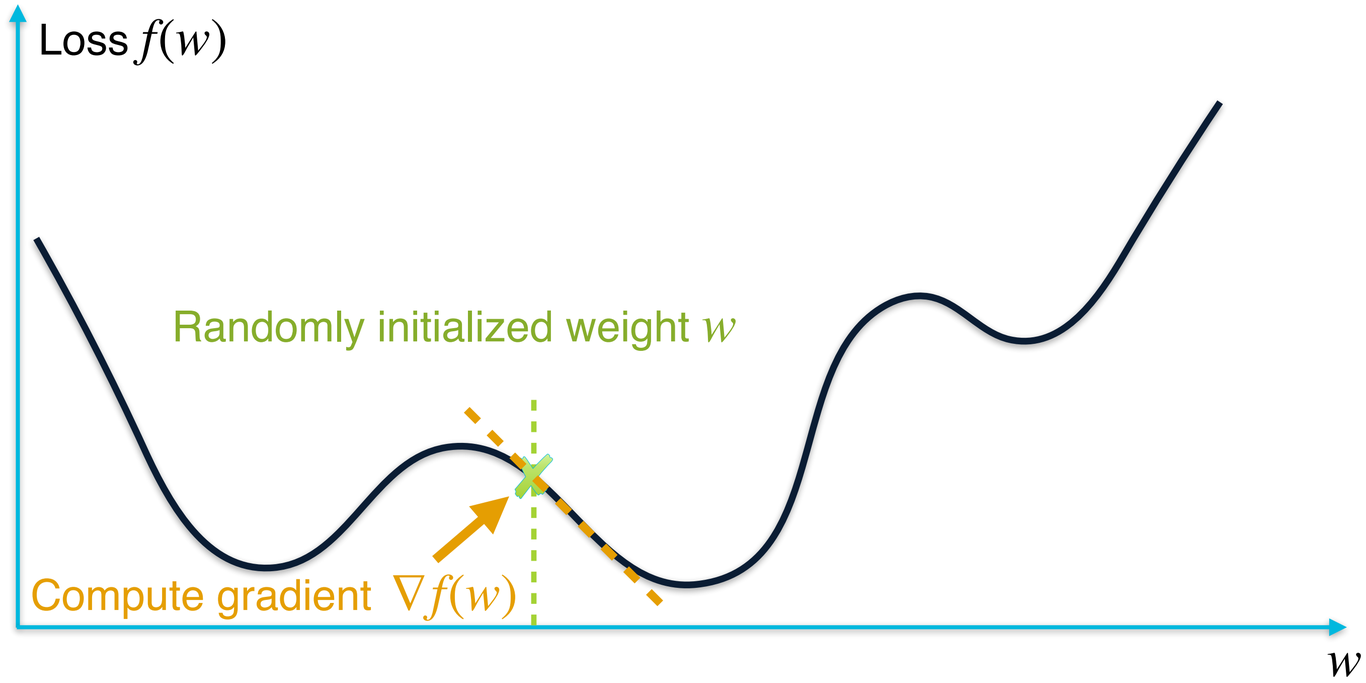

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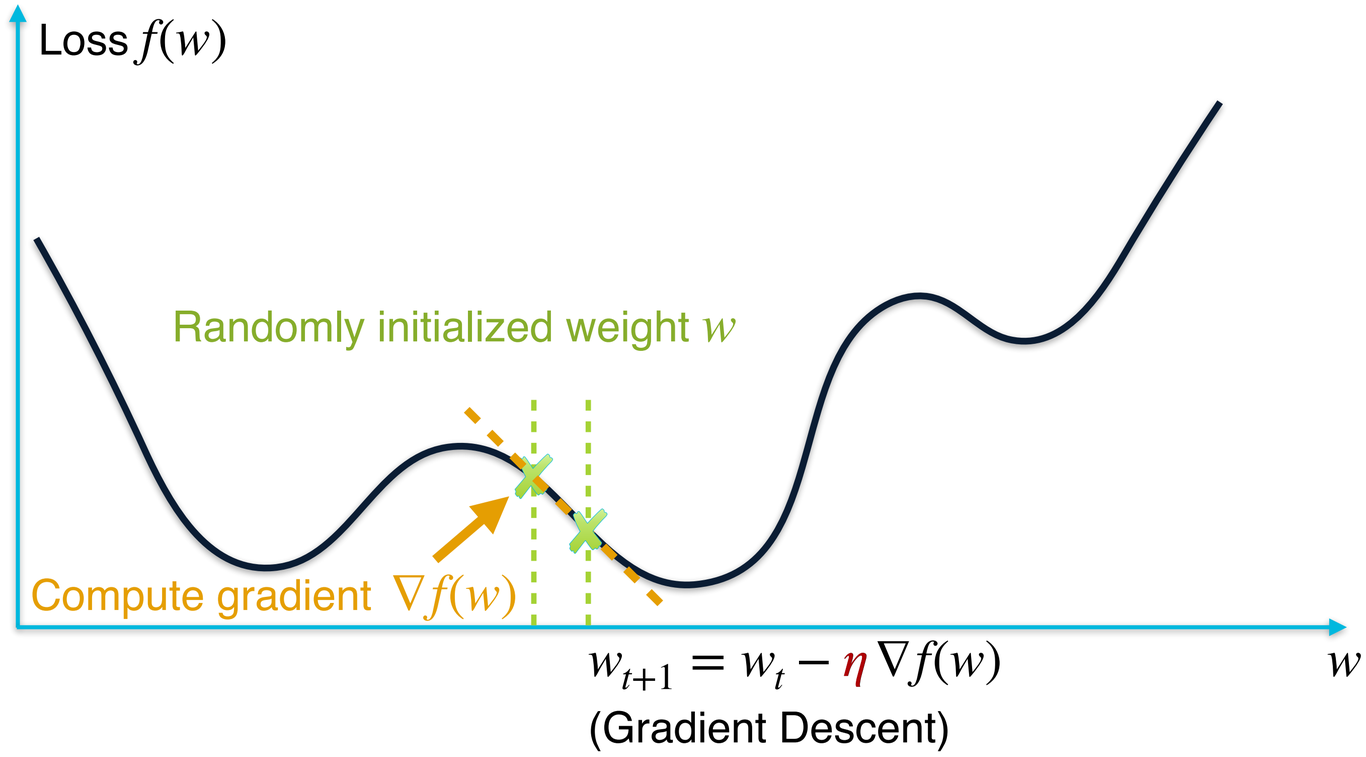

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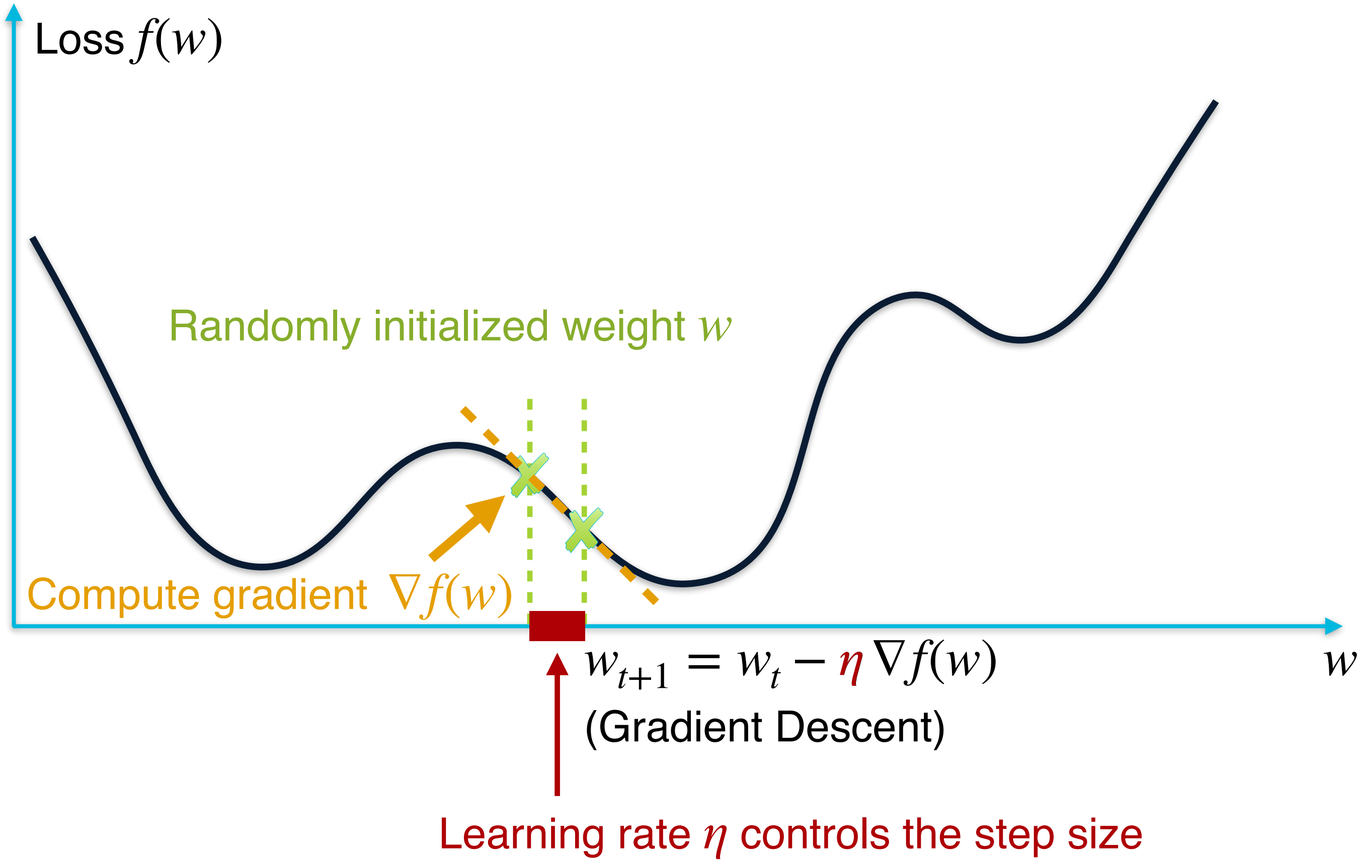
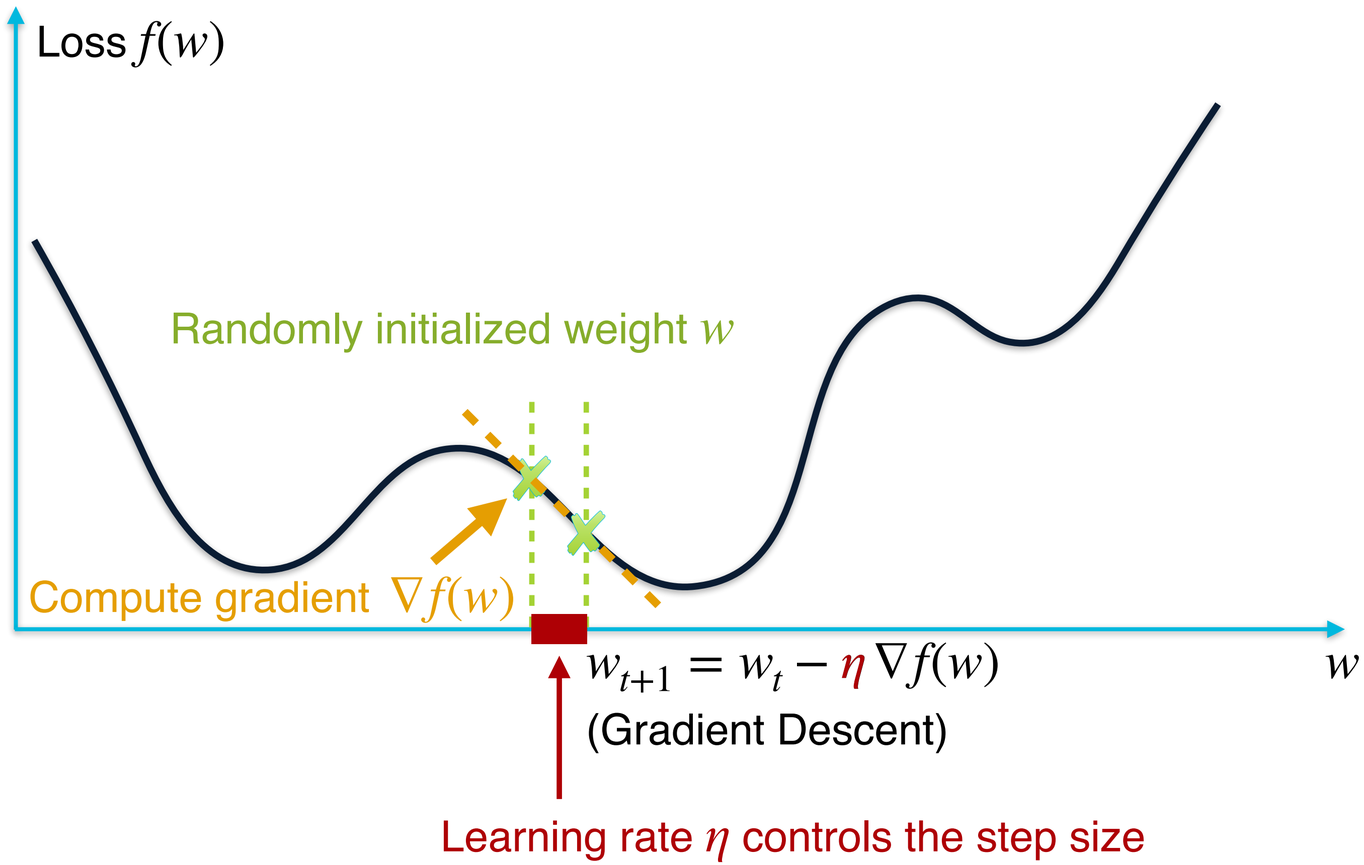


- **Solution: Gradient descent**
- **How to stop?**
  - When update is small enough
  - $\|w_{t+1} - w_t\| \leq \varepsilon$
    i.e., $\|\nabla f(w_t)\| \leq \varepsilon$



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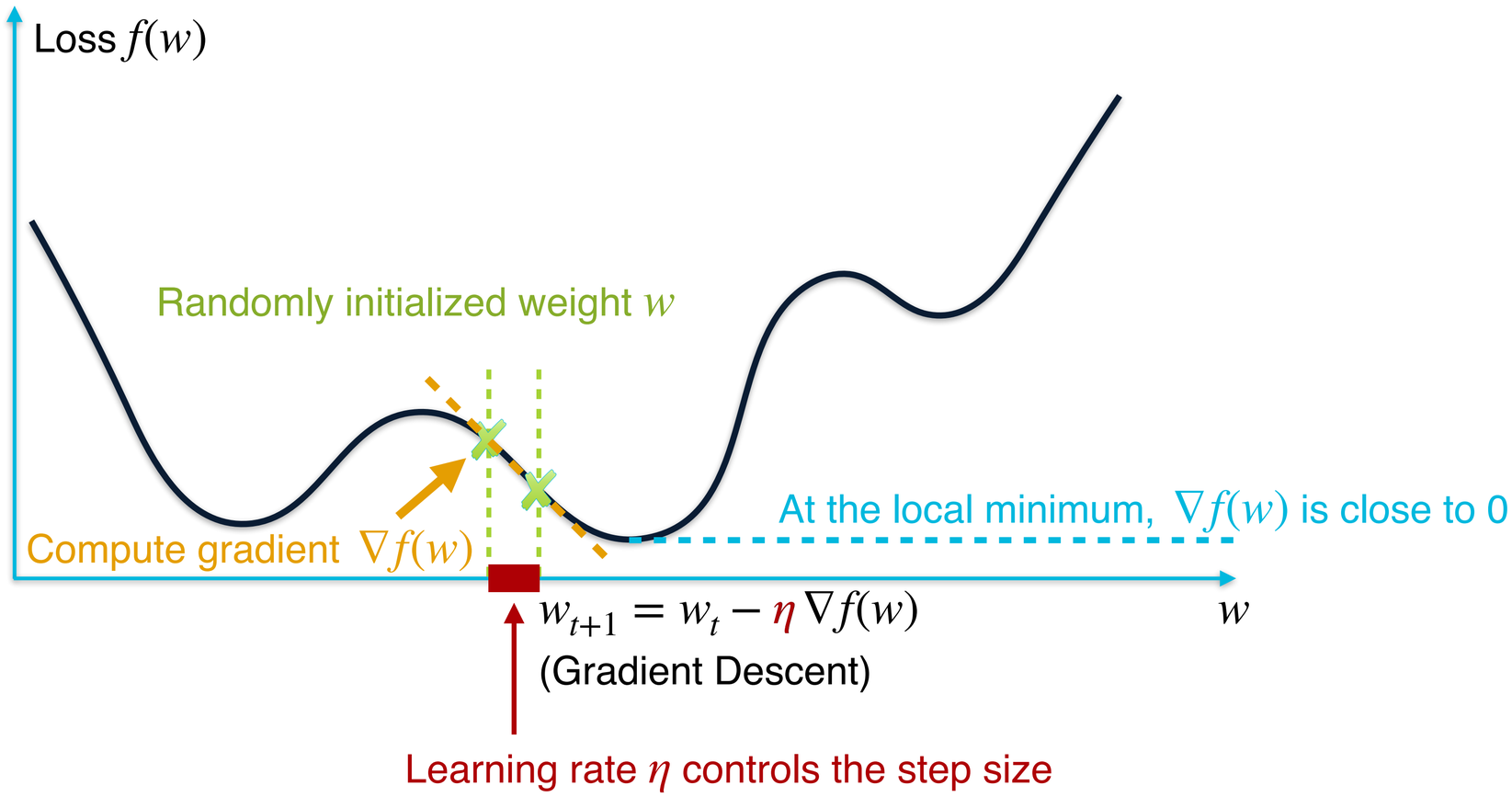

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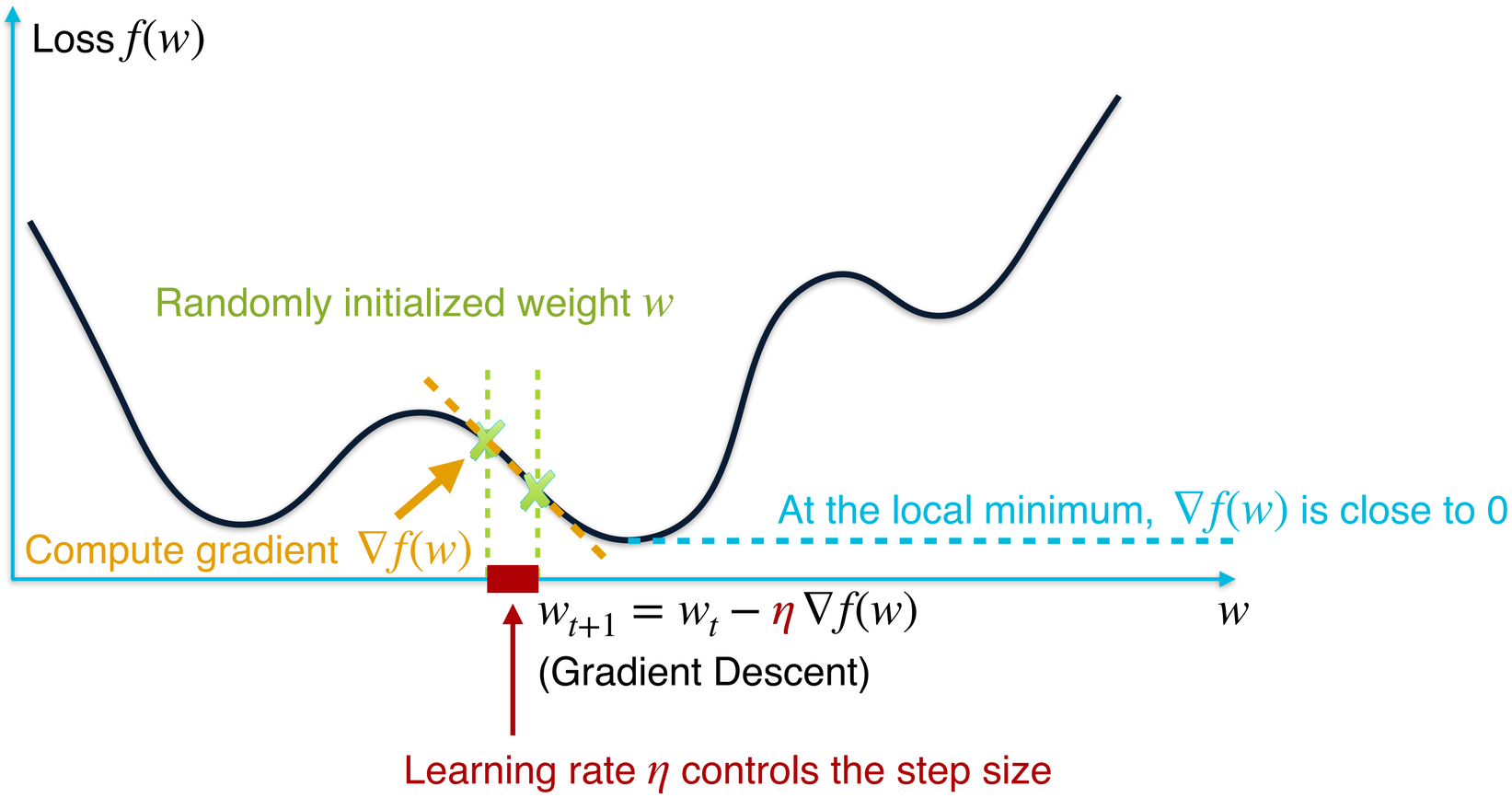
- **How to stop?**
  - When update is small enough
  - $\|w_{t+1} - w_t\| \leq \varepsilon$ i.e., $\|\nabla f(w_t)\| \leq \varepsilon$
- **Problem**
  - Usualy, the number of training sample n is large
  - Slow convergence



- **Solution: Stochastic Gradient descent**
  - At each step of gradient descent, instead of compute for all training samples, randomly pick a small subset (*mini-batch*) of training samples (x_k, y_k):

$$w_{t+1} \leftarrow w_t - \eta \nabla f(w_t, x_k, y_k)$$

- **Compared to gradient descent, SGD takes more steps to converge, but each step is much faster.**

EXAMPLE OF FEDAVG

- **In a round t**
  - The central server broadcasts current model w_t
  - Each client k computes gradient $g_k \leftarrow \nabla F_k(w_t)$, on its local data
  - In other words, each client k computes **for E epochs:** $w_{t+1}^k \leftarrow w_t - \eta \nabla g_k$
  - The central server performs aggregation

$$w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^k$$

- **Suppose B is the local mini-batch size,**

  #updates on client k in each round: $u_k = E\frac{n_k}{B}$

Algorithm 1 `FederatedAveraging`. The K clients are indexed by k; B is the local minibatch size, E is the number of local epochs, and η is the learning rate.

Server executes:

initialize w_0

for each round $t = 1, 2, \dots$ **do**

$m \leftarrow \max(C \cdot K, 1)$

$S_t \leftarrow$ (random set of m clients)

for each client $k \in S_t$ **in parallel do**

$w_{t+1}^k \leftarrow \text{ClientUpdate}(k, w_t)$

$w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^k$

ClientUpdate(k, w): *// Run on client k*

$\mathcal{B} \leftarrow$ (split $\mathcal{P}_k$ into batches of size B)

for each local epoch i from 1 to E **do**

for batch $b \in \mathcal{B}$ **do**

$w \leftarrow w - \eta \nabla \ell(w; b)$

return w to server

FEDERATED LEARNING
CHALLENGES AND FEATURES

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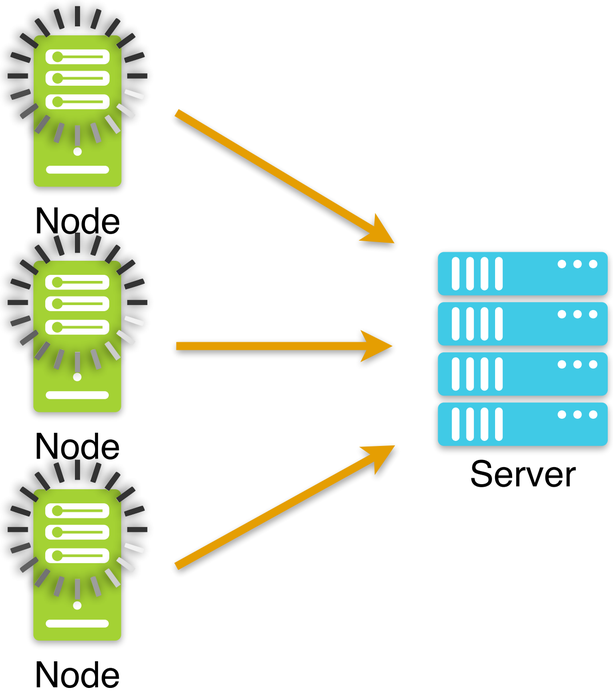
FEDERATED LEARNING CHALLENGES

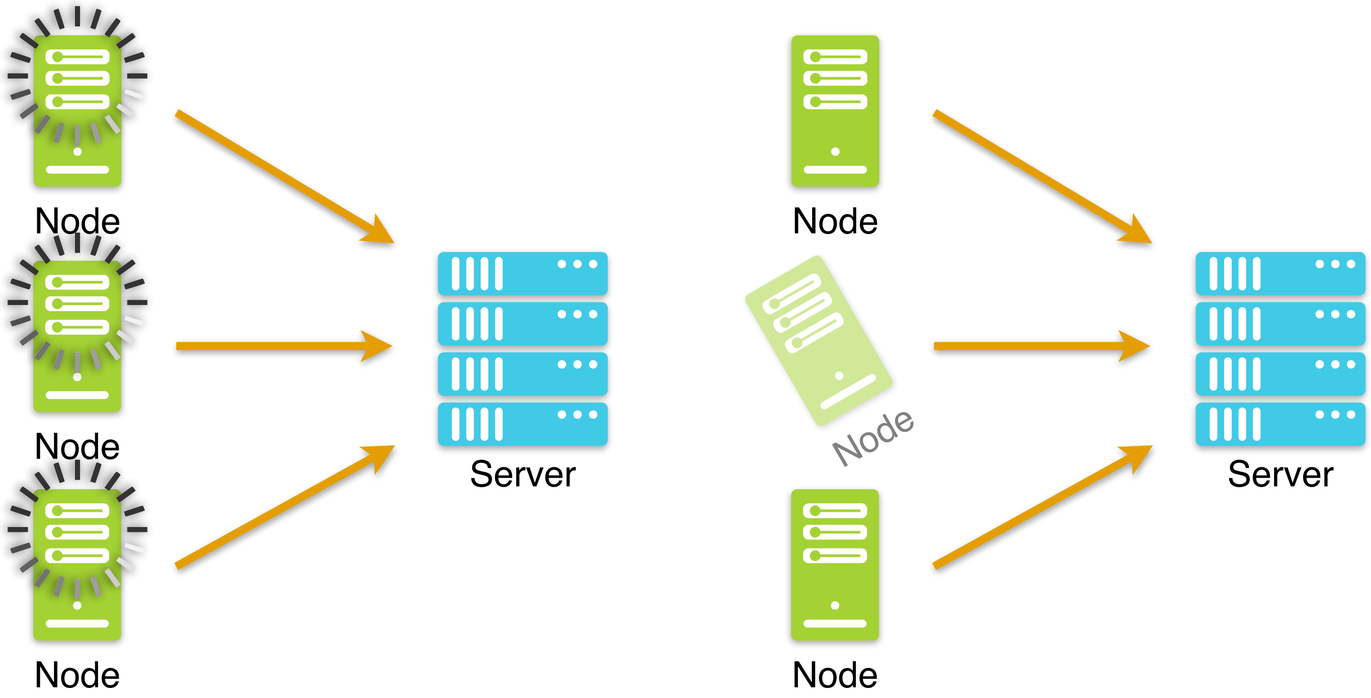
System issues

System issues



Power consumption

System issues



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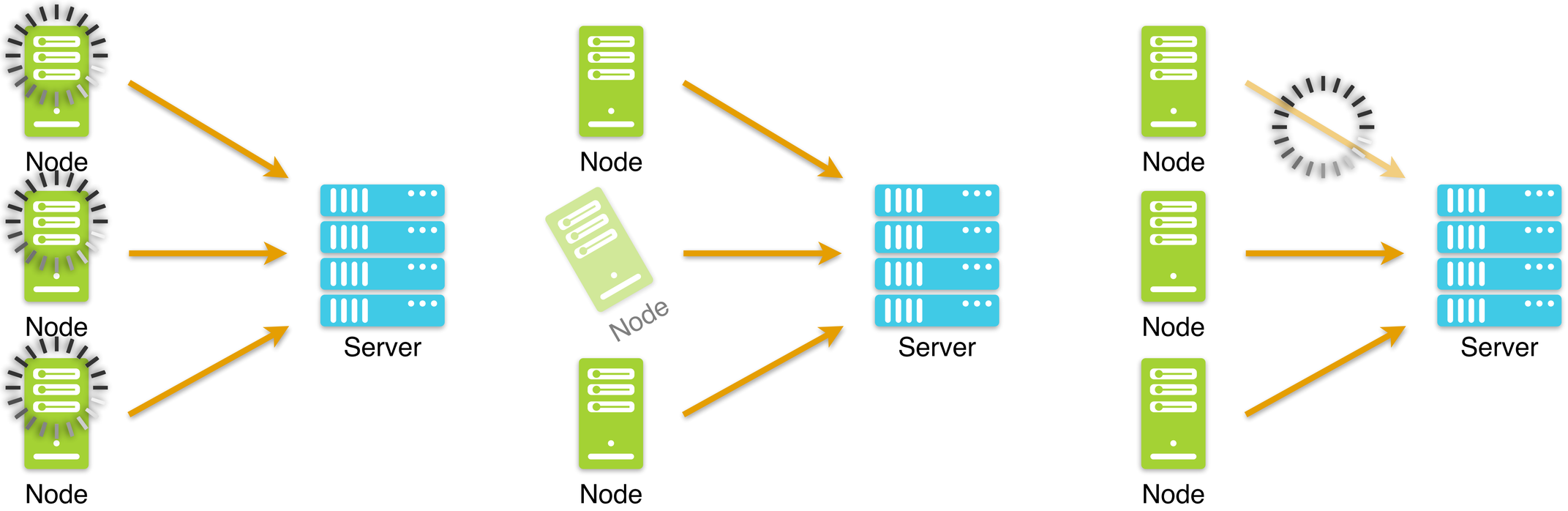
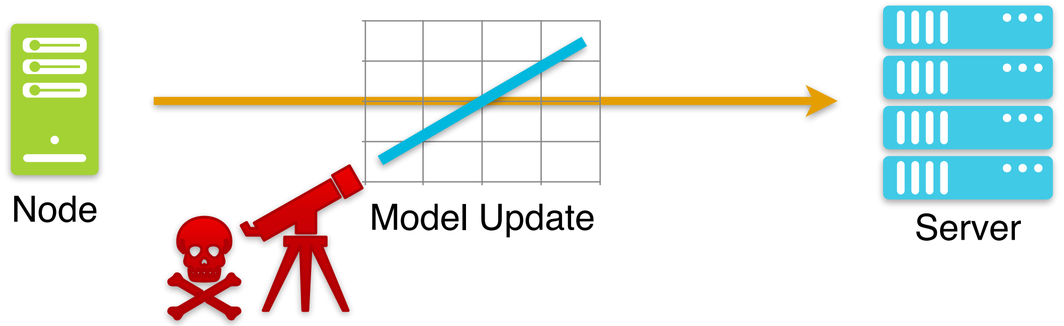


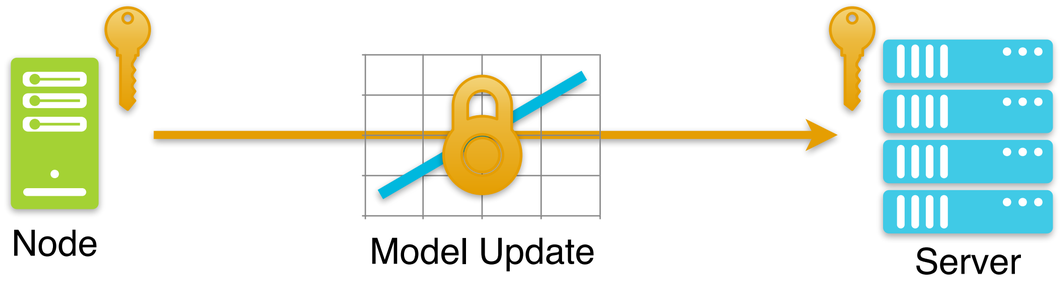
FEDERATED LEARNING CHALLENGES

Privacy issues

- **Privacy issues**
  - Man in the middle



- **Privacy issues**
  - Man in the middle
    - End-to-end encryption



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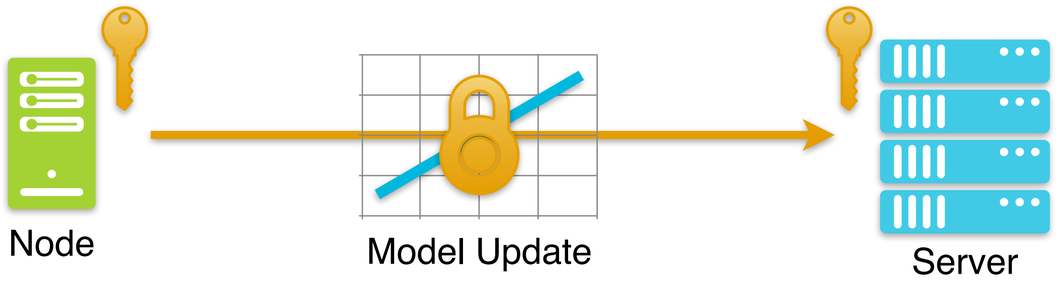
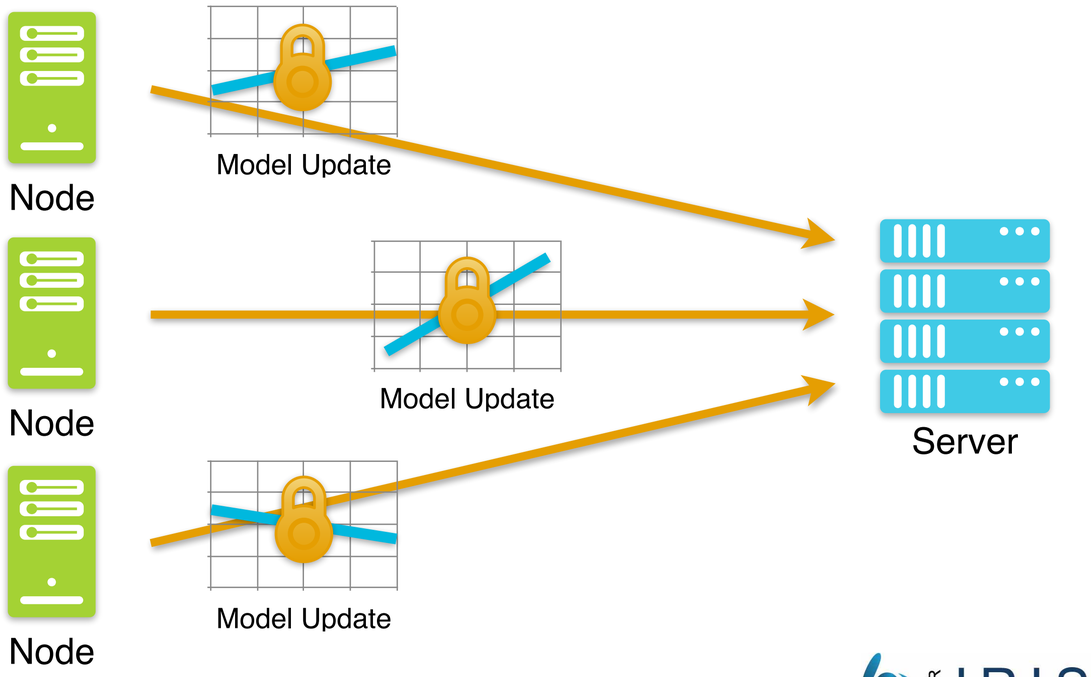


- Honest-but-curious server



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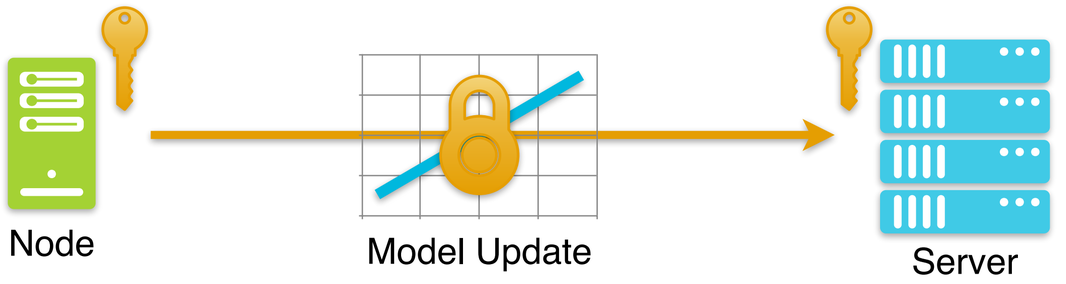

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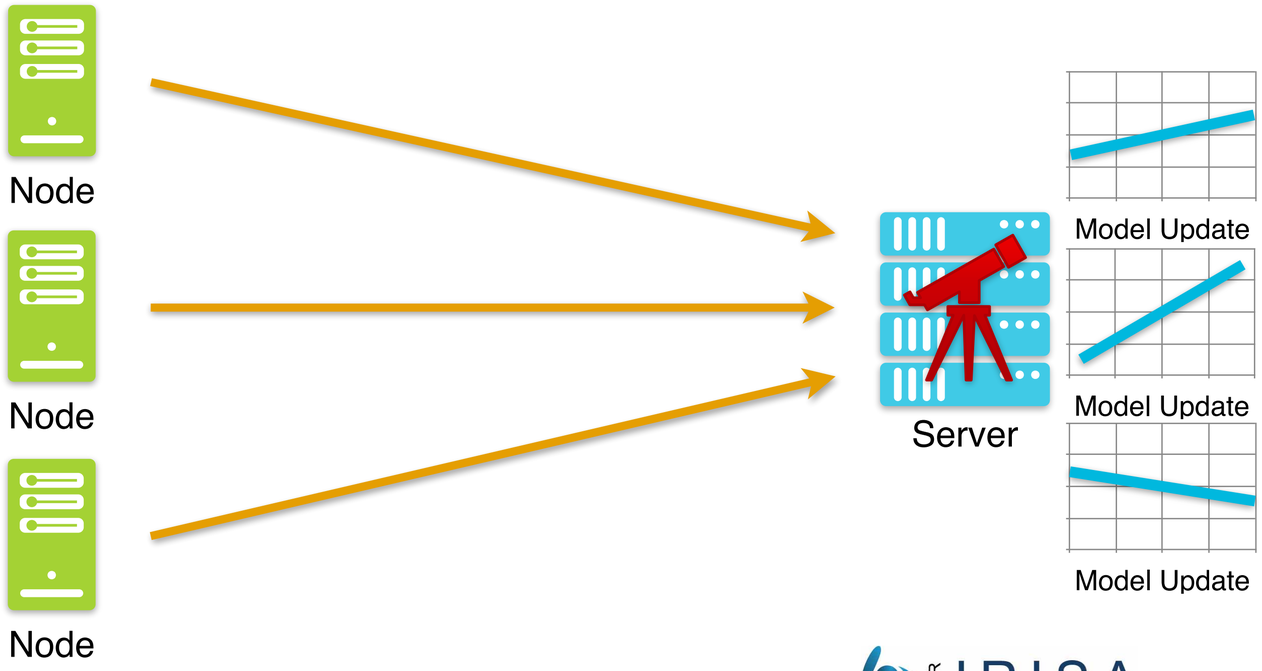

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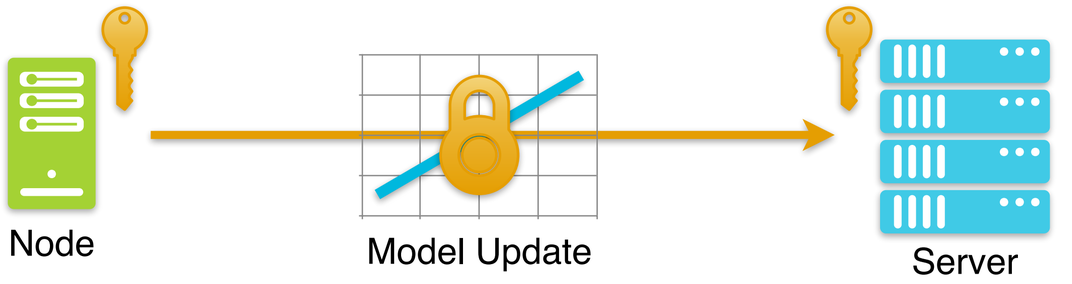

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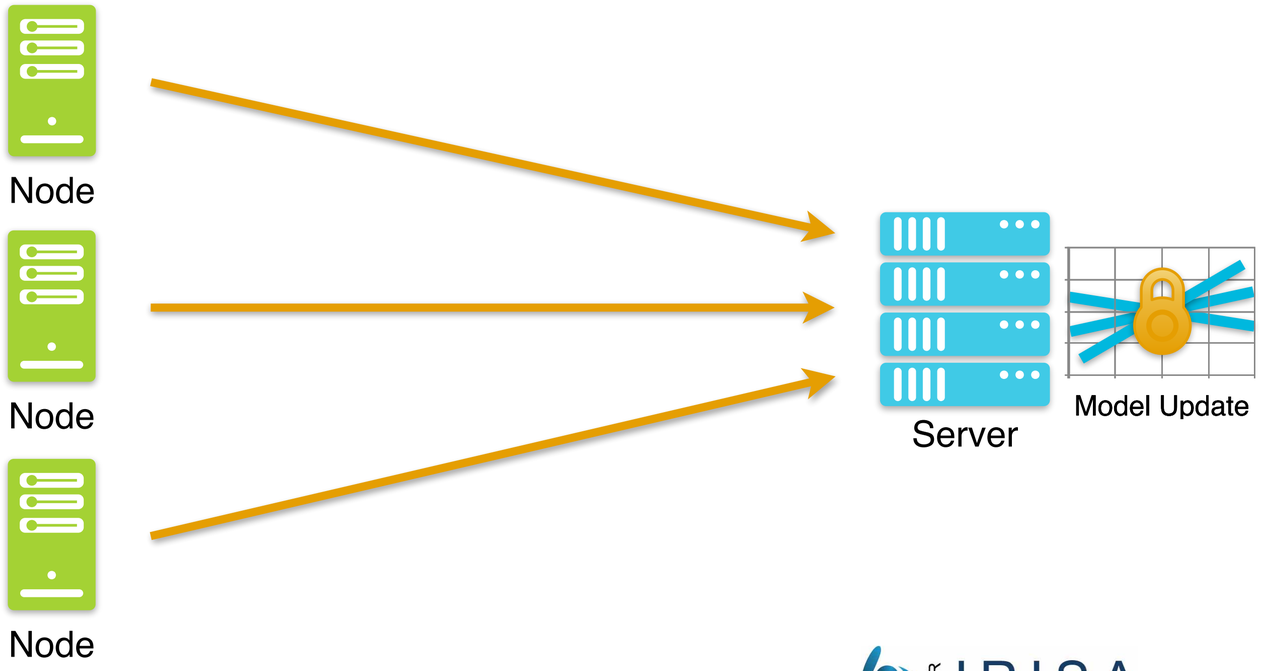
    - Secure aggregation



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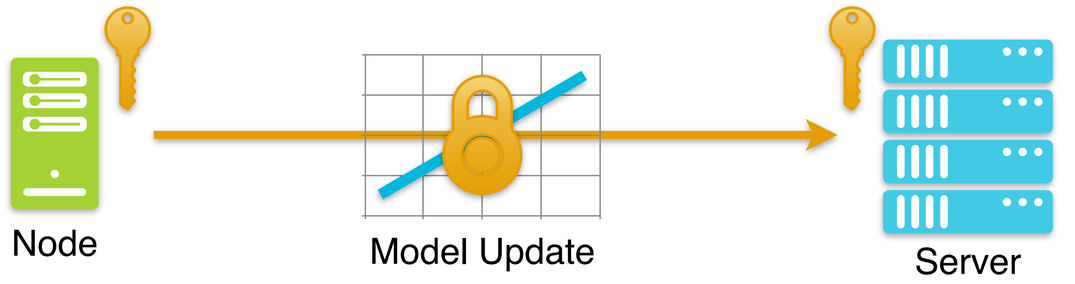

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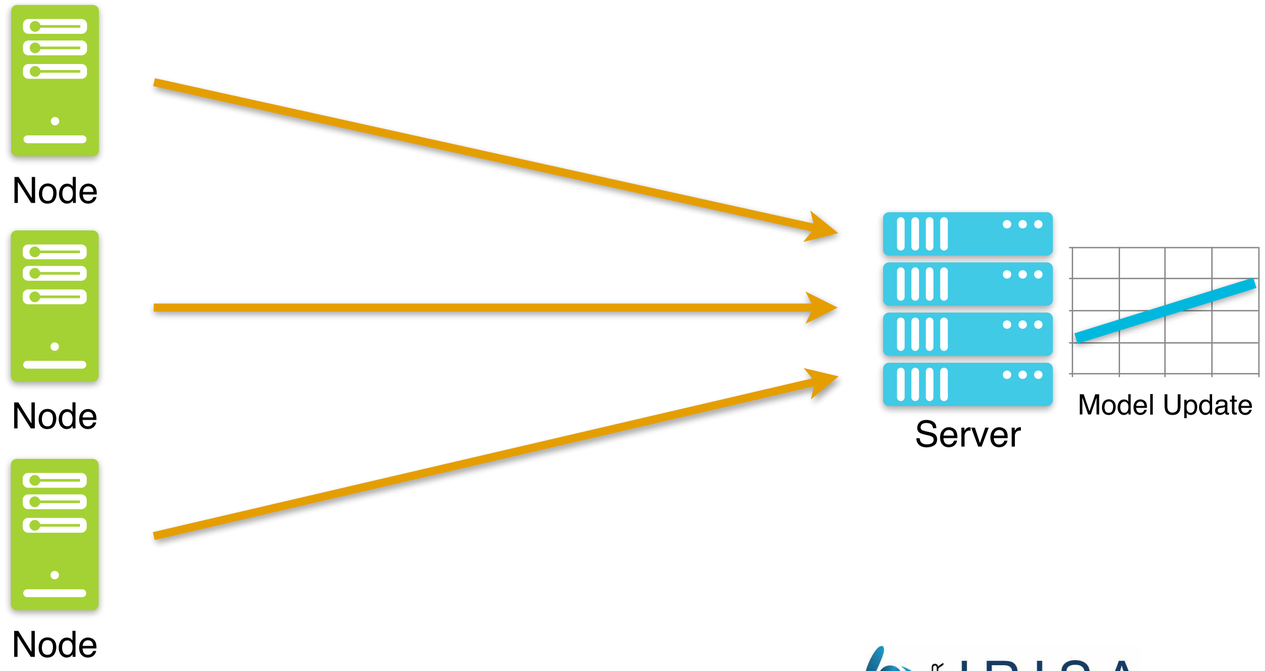

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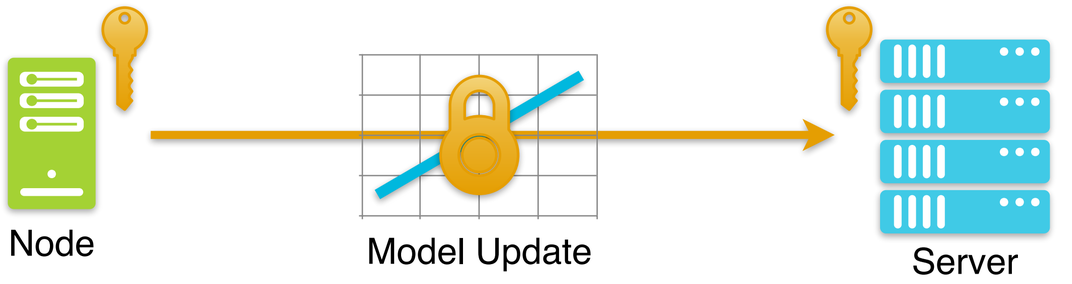
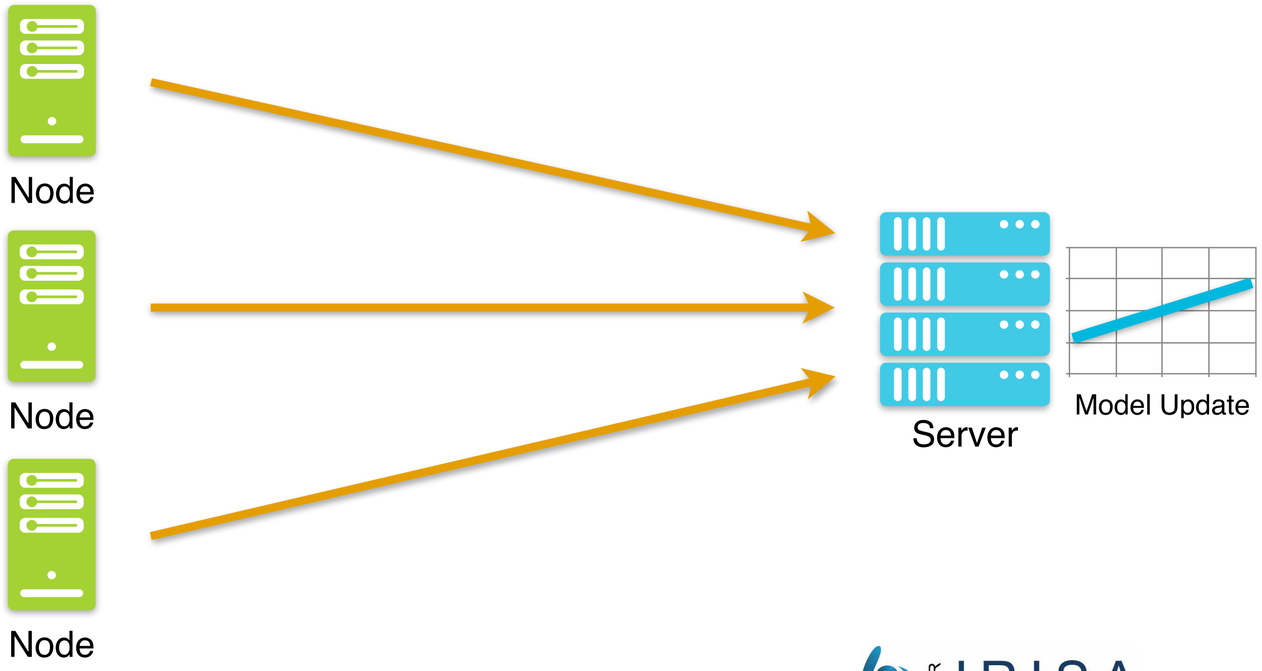
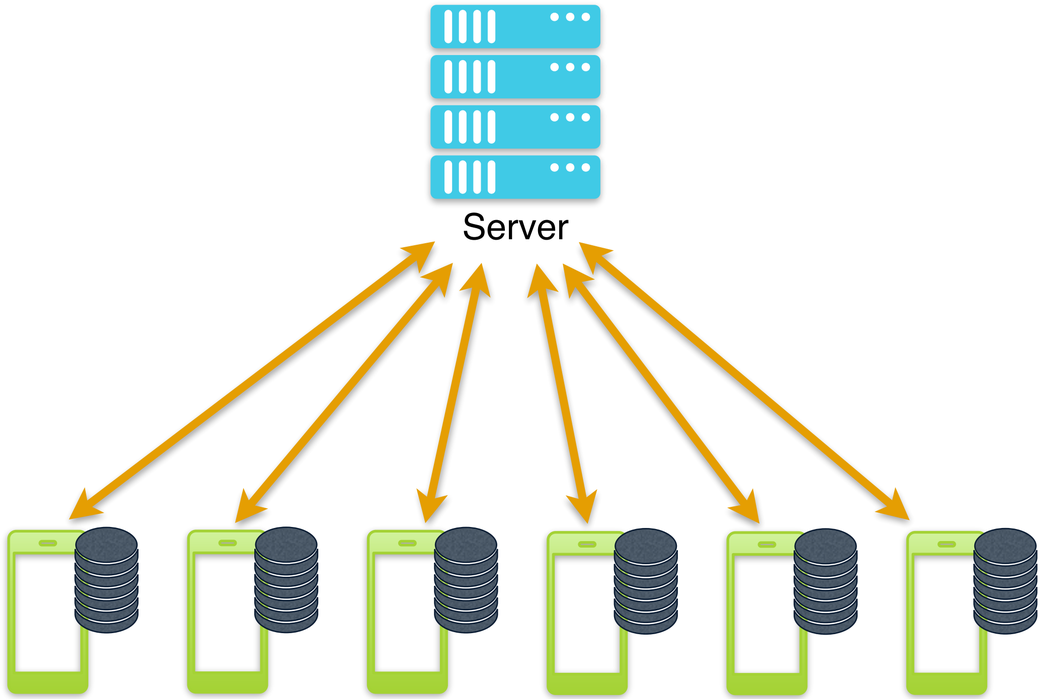


  - Honest-but-curious server
    - Secure aggregation
    - Differential Privacy for increased security



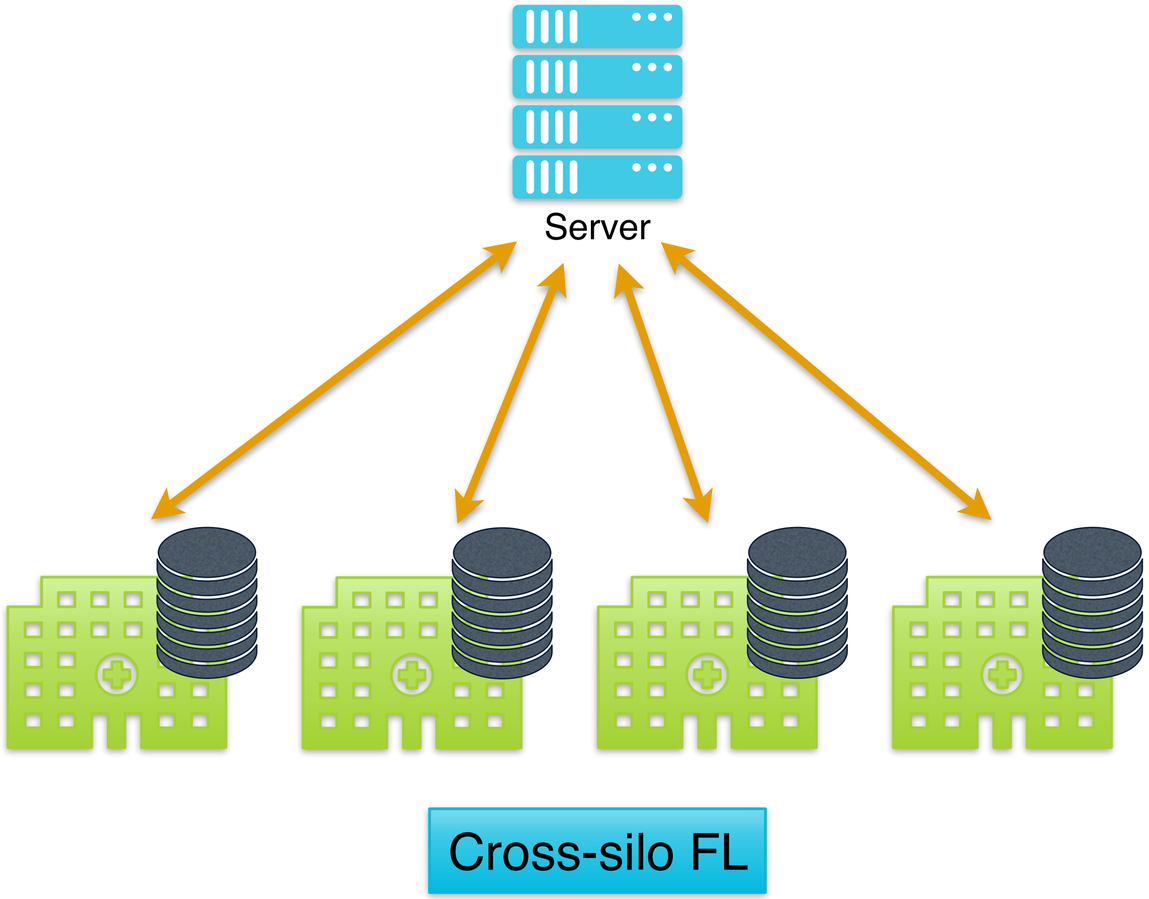
CROSS-DEVICE VS CROSS-SILO FL



Cross-device FL

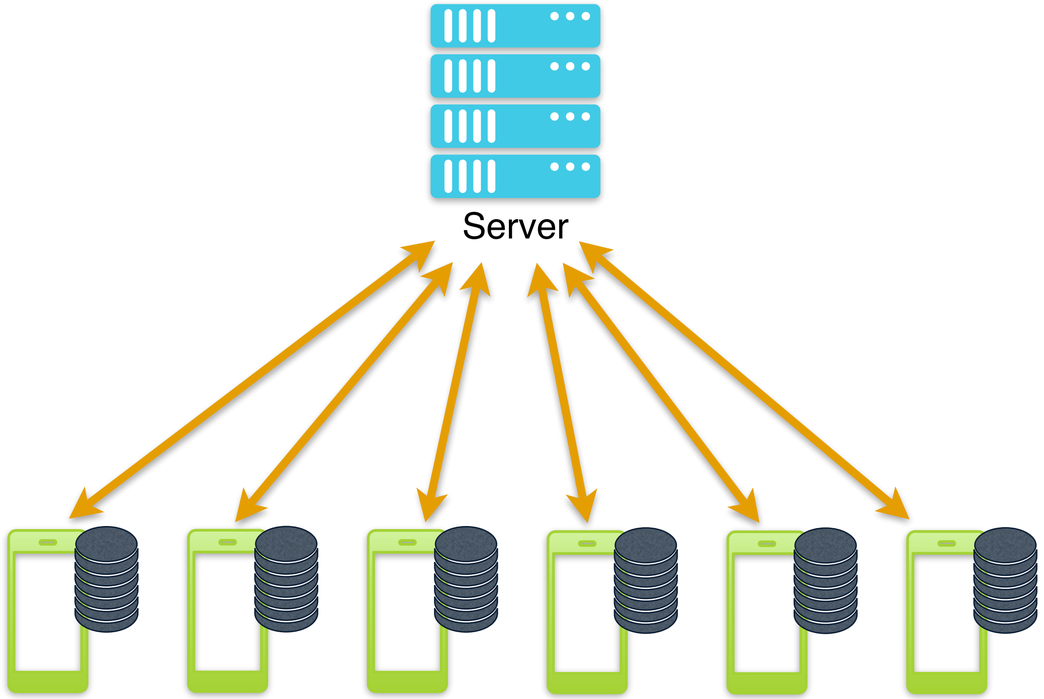
- **Massive number of parties**
  - up to 10^{10}
- **Small dataset per party**
  - could be size 1
- **Limited availability and reliability**
- **Some parties may be malicious**

CROSS-DEVICE VS CROSS-SILO FL

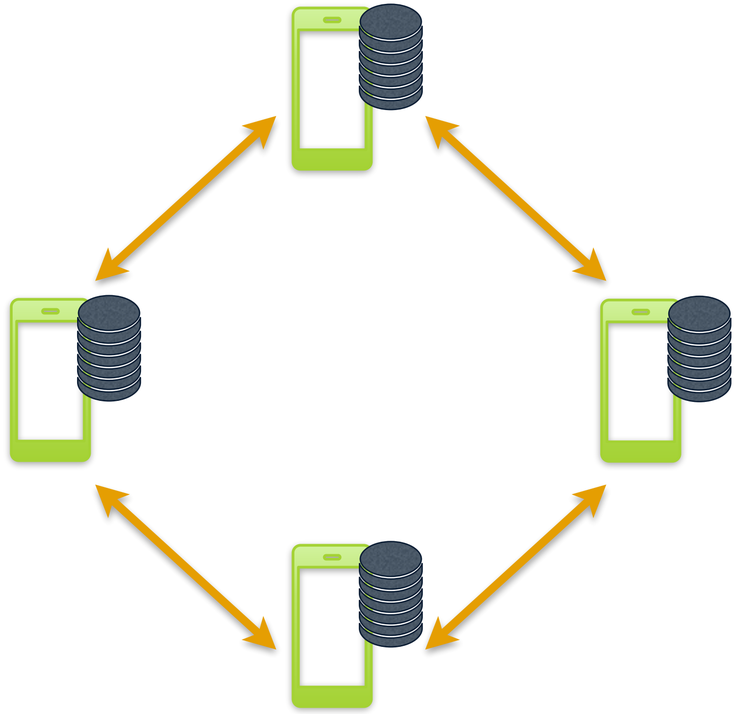


- **2-100 parties**
- **Medium to large dataset per party**
- **Reliable parties**
  - Almost always available
- **Parties are typically honest**

SERVER ORCHESTRATED VS. FULLY DECENTRALIZED FL



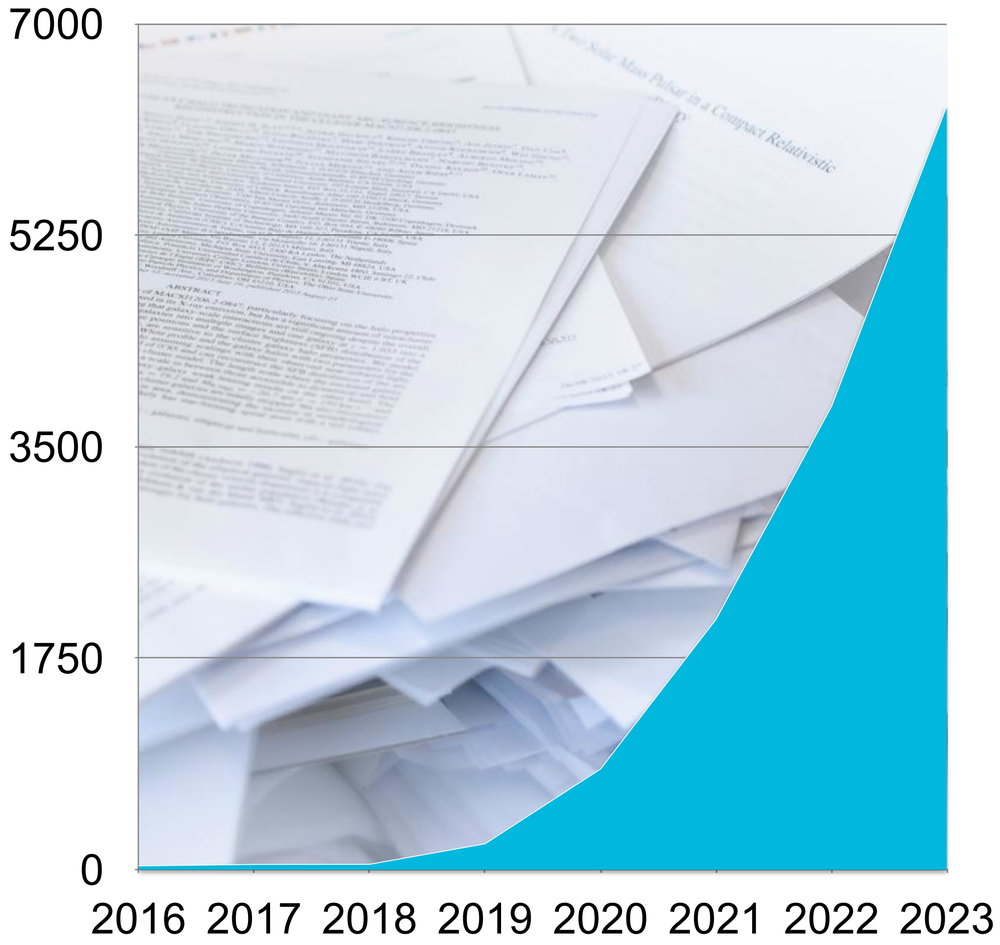
- Server-client communication
- Global coordination, global aggregation
- Server is a single point of failure and may become a bottleneck



- Device-to-device communication
- No global coordination, local aggregation
- Naturally scales to a large number of devices

FEDERATED LEARNING IS A BOOMING TOPIC

- **Historical**
  - 2016: the term FL is first coined by Google researchers
  - 2018: « just » 45 papers on FL (*source: Scopus*)
  - 2023: more than 6k papers on FL! (*source: Scopus*)
- **Some real-world deployments by companies and researchers**
- **Several open-source libraries are under development:**
  - Flower, PySyft, TensorFlow Federated, FATE, Substra...
- **FL is highly multidisciplinary**
  - Involve machine learning, numerical optimization, privacy & security, networks, systems, hardware...



HANDS-ON! — PART 1

FEDERATED LEARNING IN A NUTSHELL

SCAN ME

https://bit.ly/FLxSec-part1

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THE POWER OF FEDERATED LEARNING FOR NETWORK SECURITY

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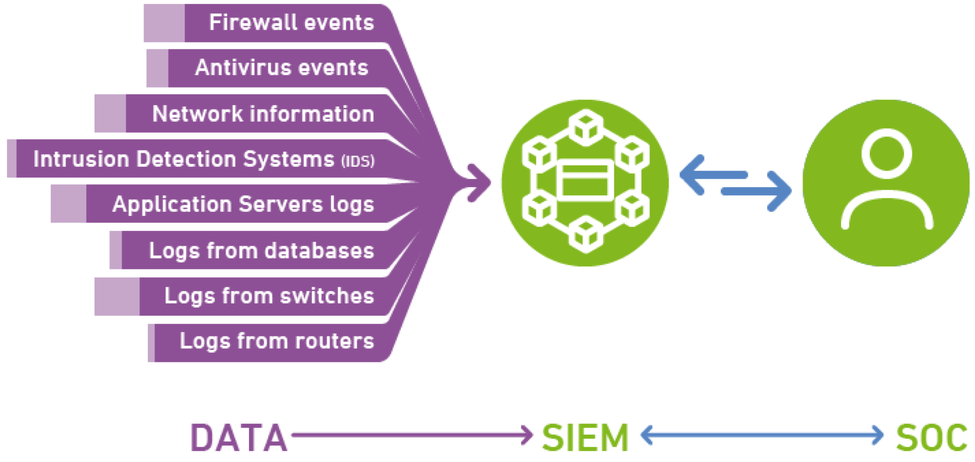
INVOLVEMENT OF AI IN CYBER-ATTACK DETECTION

- **How recent artificial intelligence methods can be applied to cyber-attacks?**
  - Drastically improve detection and even remediation mechanisms
  - Take into account 0-day vulnerabilities and attacks

- **SOC/SIEM level in particular**
  - Detection of APT or Smart-DDoS for instance

- **Federated/collaborative approaches**
  - Federated Learning for Cyber-Attack Detection



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* SIEM = Security Information and Event Management
* APT = Advanced Persistent Threat
* DDoS = Distributed Denial of Service

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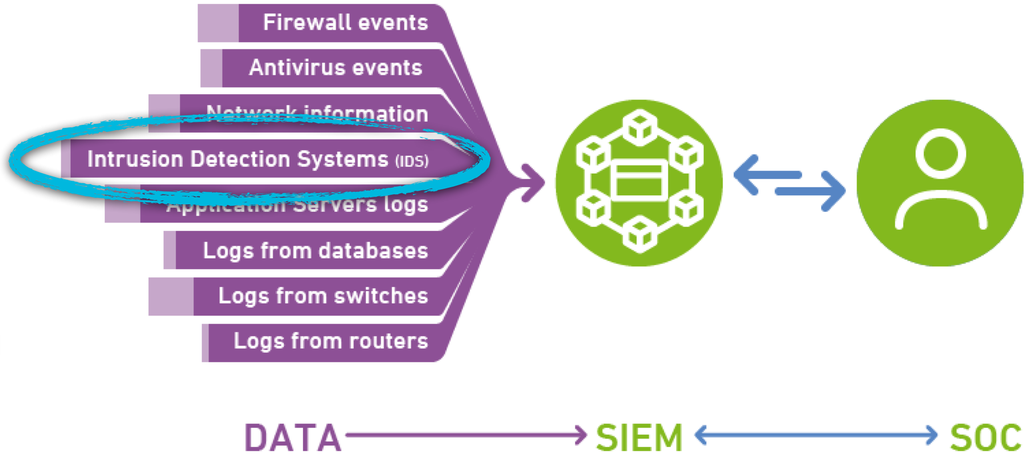

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USE-CASE: INTRUSION DETECTION

- **Different families:**
  - misuse detection, anomaly detection, specification-based…
- **Machine learning (ML) and deep learning (DL) often used for their performance**
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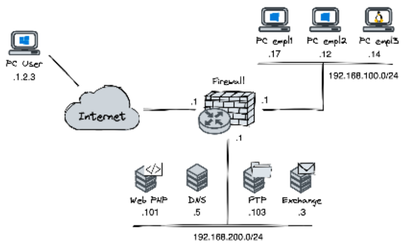

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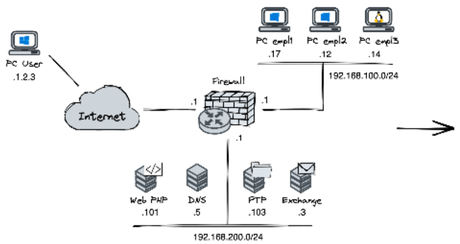
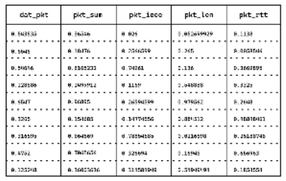


2. Data curation



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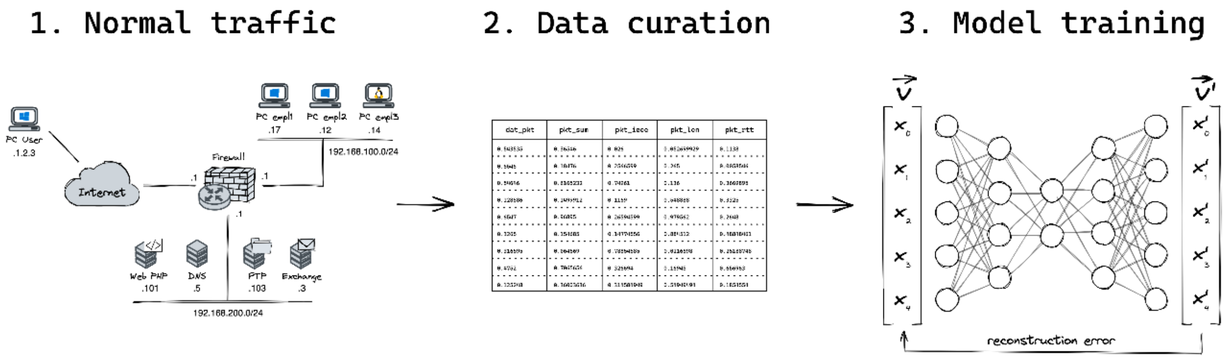

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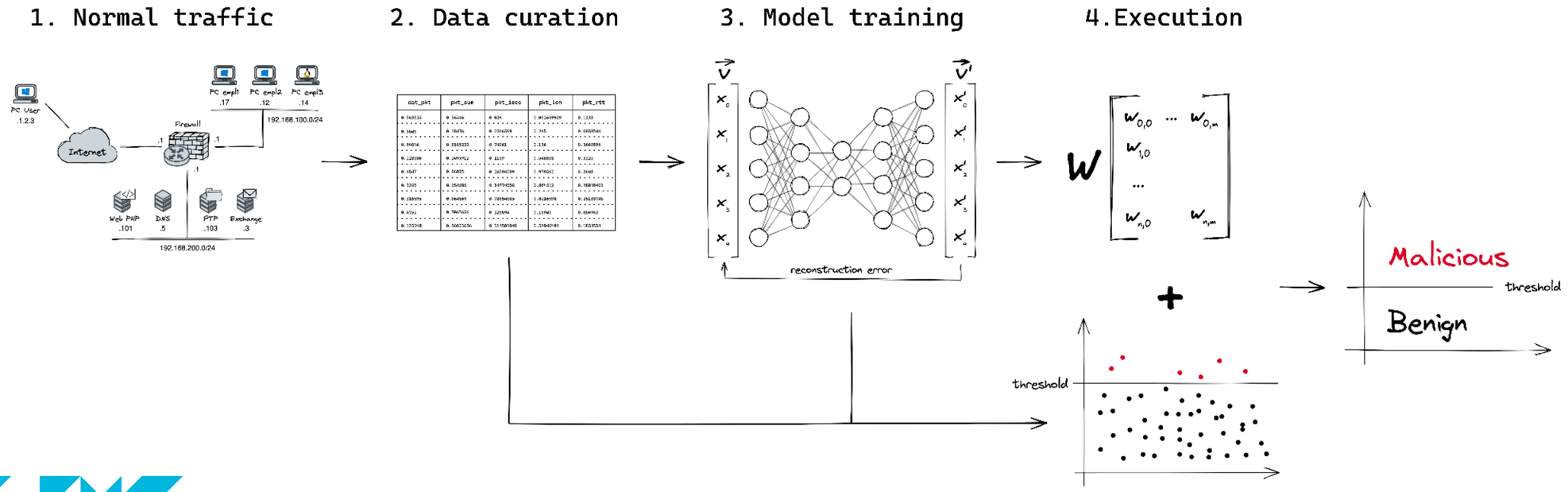

CURRENT INDUSTRIAL APPROACH

- **Intrusion Detection System (IDS) & Security Information and Event Management (SIEM)**
  - Individual alerts without context
  - Investigation leads analysts to alert fatigue

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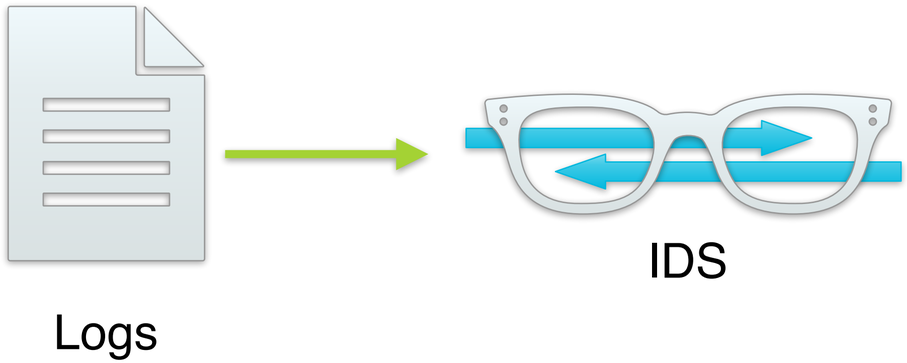
Logs

- **Intrusion Detection System (IDS) & Security Information and Event Management (SIEM)**
  - Individual alerts without context
  - Investigation leads analysts to alert fatigue



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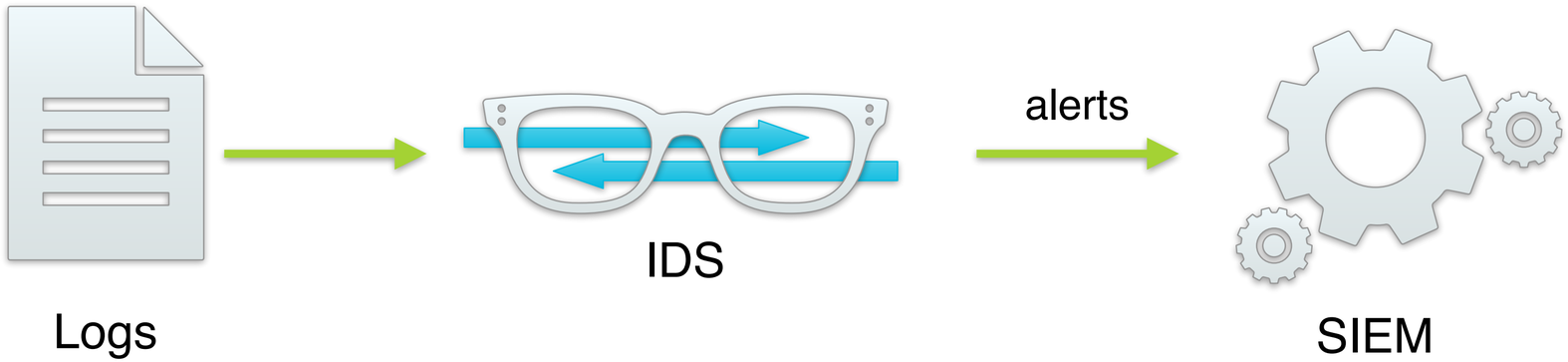

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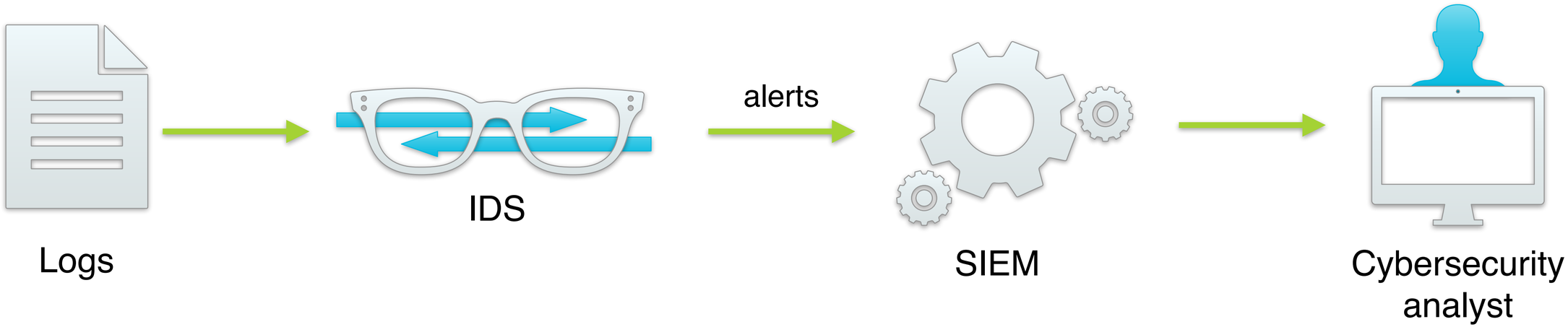

CURRENT INDUSTRIAL APPROACH

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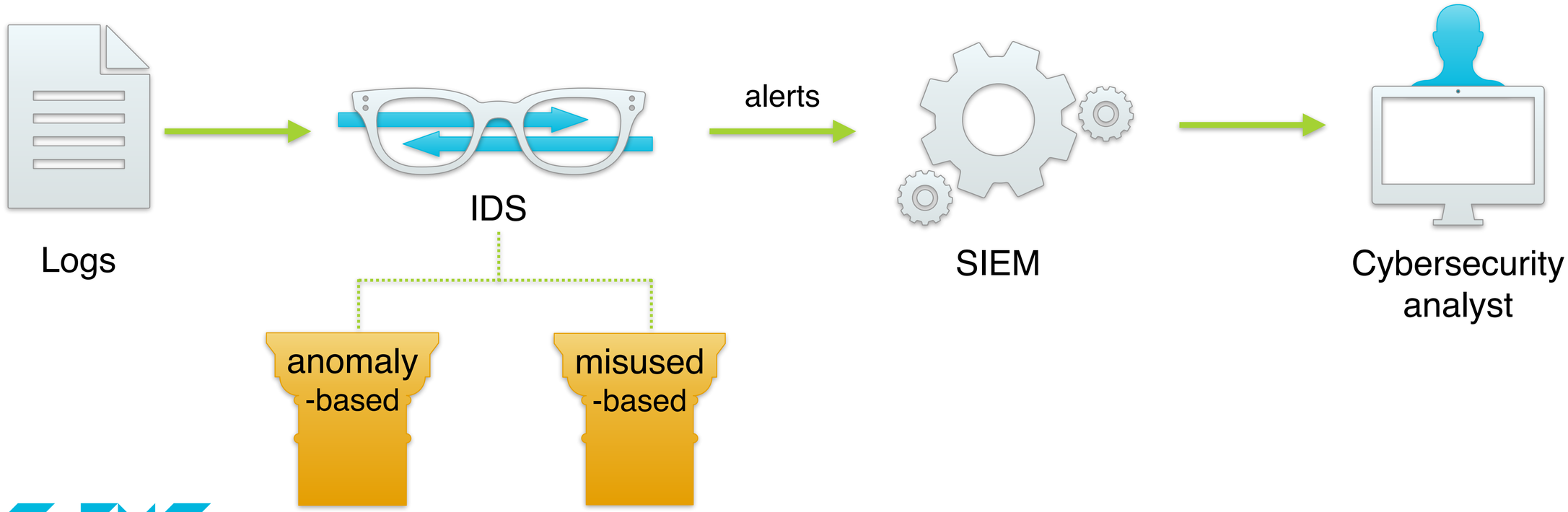
  - Individual alerts without context
  - Investigation leads analysts to alert fatigue



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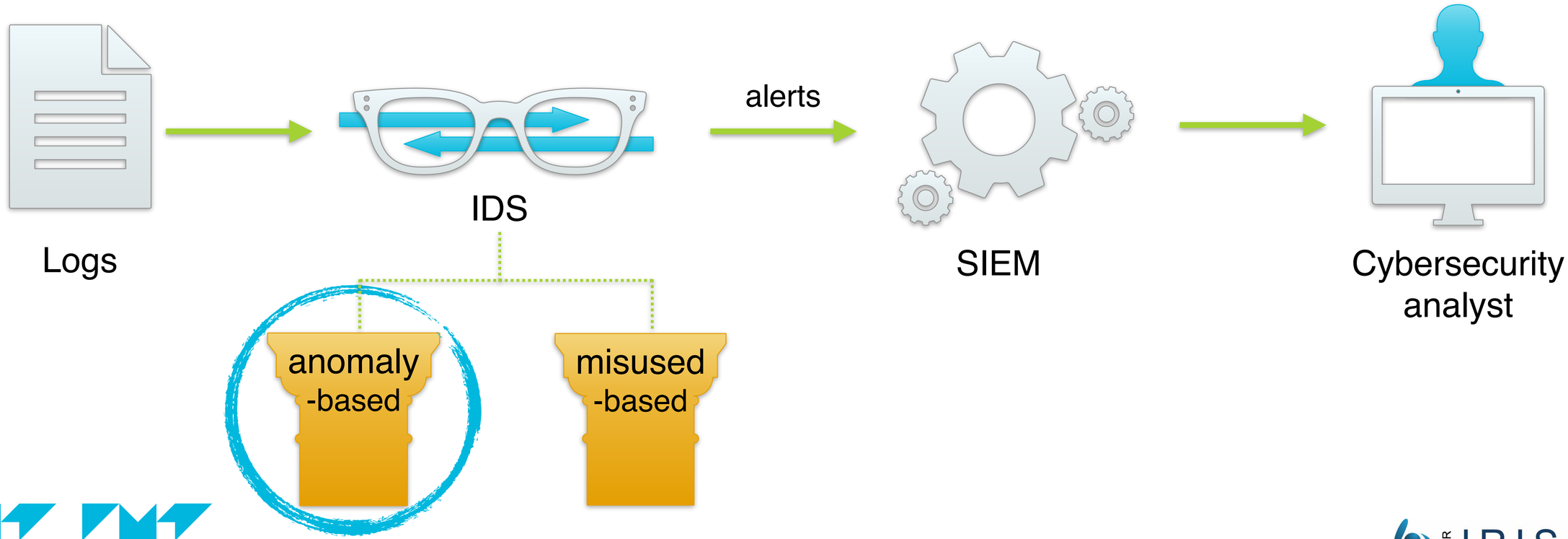


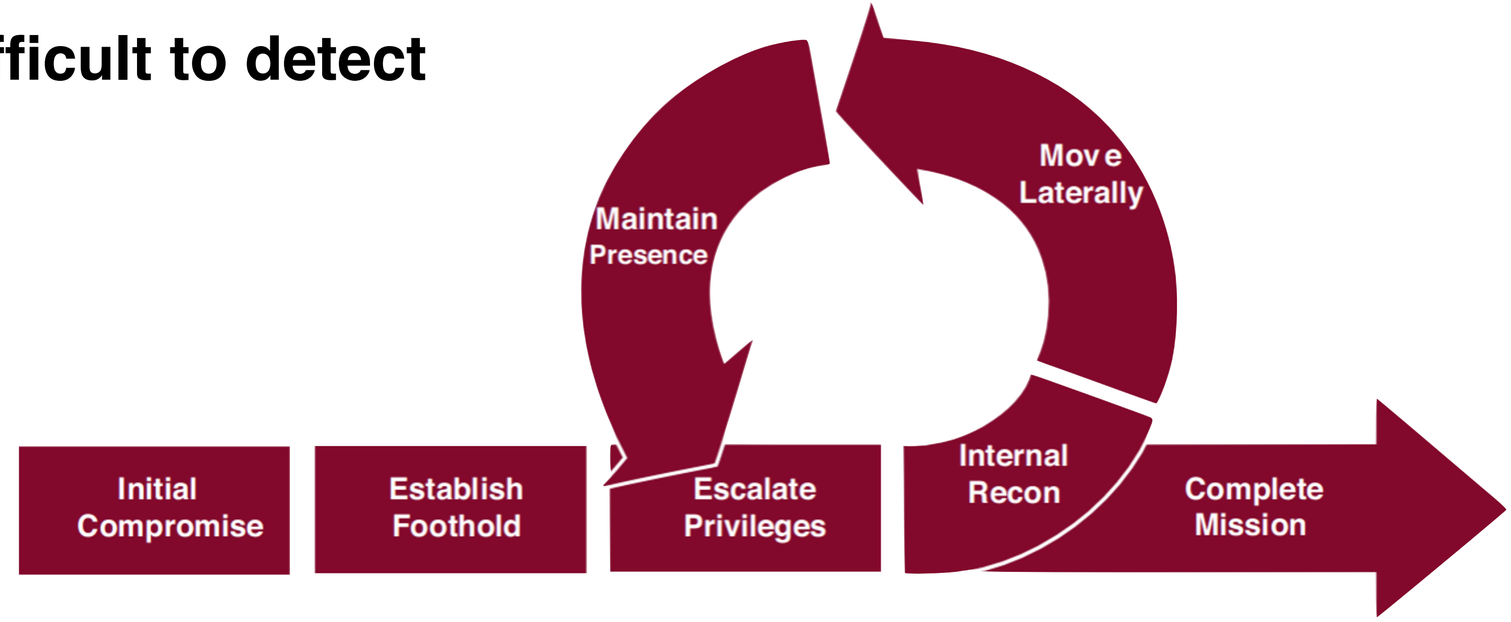
MULTI-STEP ATTACKS: EXTRACTION OF PROBABLE SCENARIOS BY CORRELATION OF ALERTS

JOINT WORK WITH YANN BUSNEL (IMT NORD EUROPE)
ANTOINE REBSTOCK, ROMARIC LUDINARD (IMT ATLANTIQUE)
& STÉPHANE PAQUELET (IRT B<>COM)

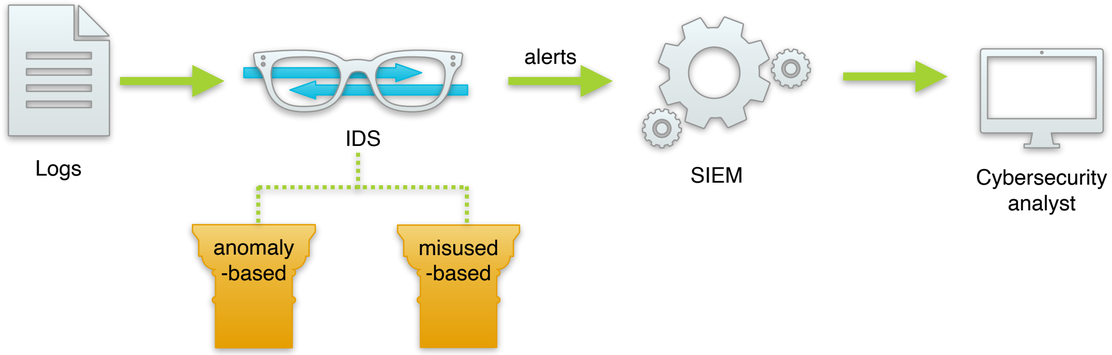
IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

- **APT = Advanced Persistent Threat**
  - Attacker usually has to perform **several actions consecutive actions**
  - As known as **multi-step attacks** and can potentially go **undetected for a long time**
  - Some of the steps of the attack can potentially be seen as a **legitimate set of actions**
- **More difficult to detect**



ON THE ROAD TO AUTOMATIC DETECTION



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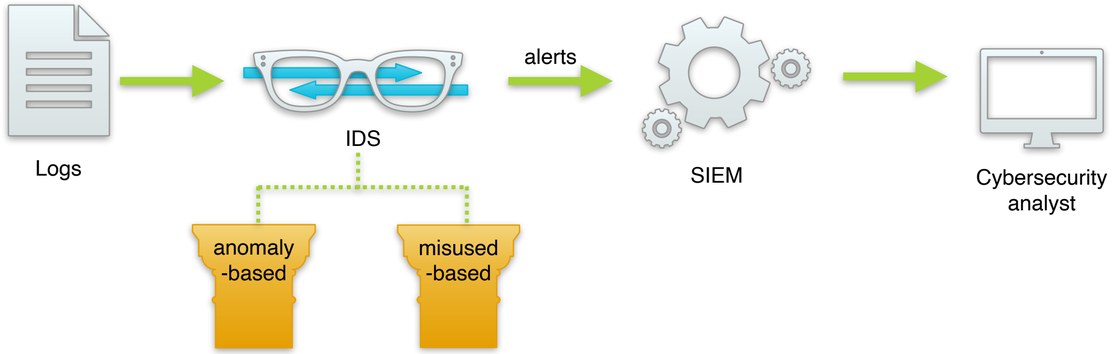
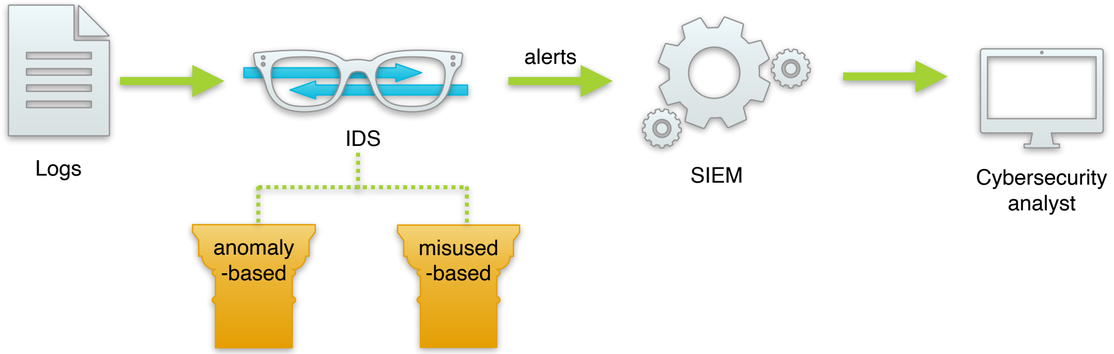


Stage 1

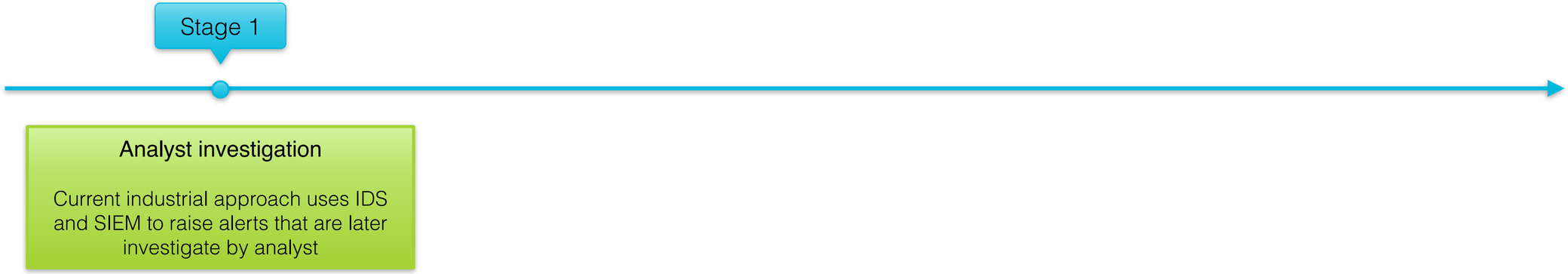
Analyst investigation

Current industrial approach uses IDS and SIEM to raise alerts that are later investigate by analyst

ON THE ROAD TO AUTOMATIC DETECTION



	Case-based
Human knowledge	✓
Unknown attacks detection	✗



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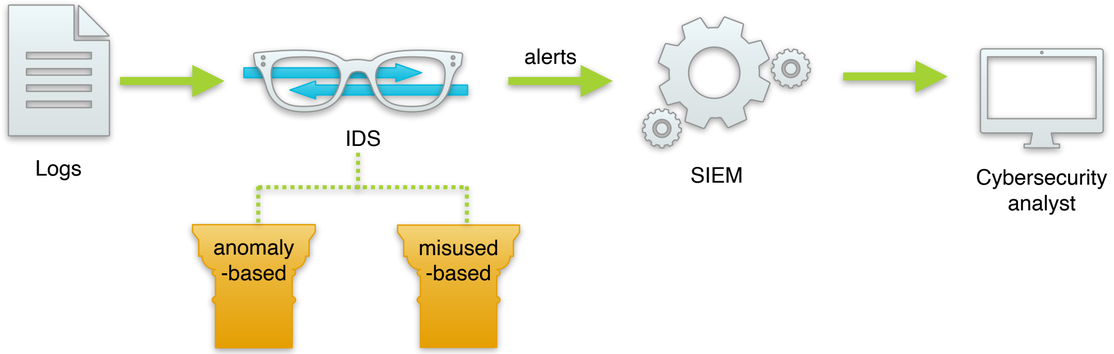

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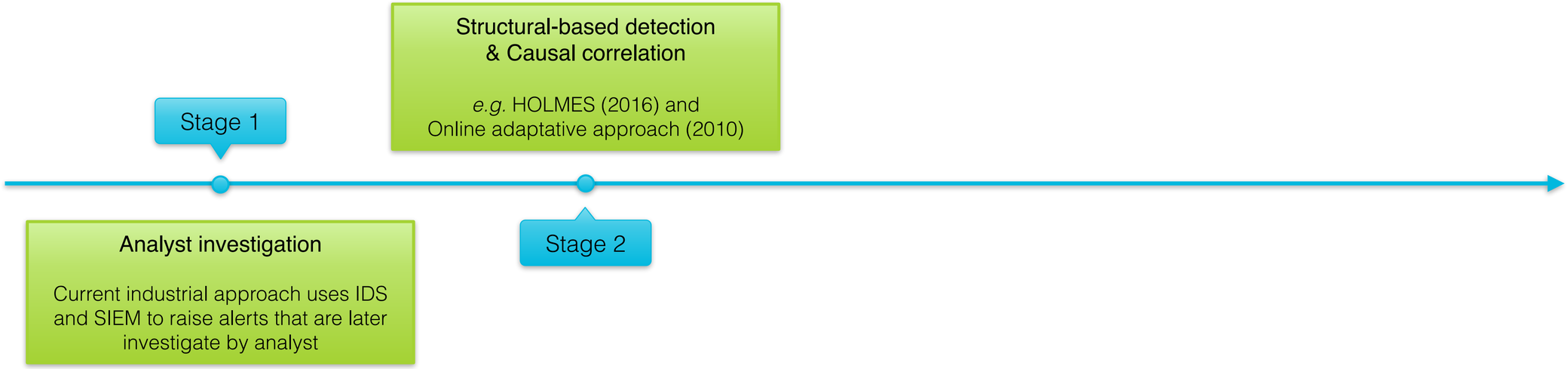

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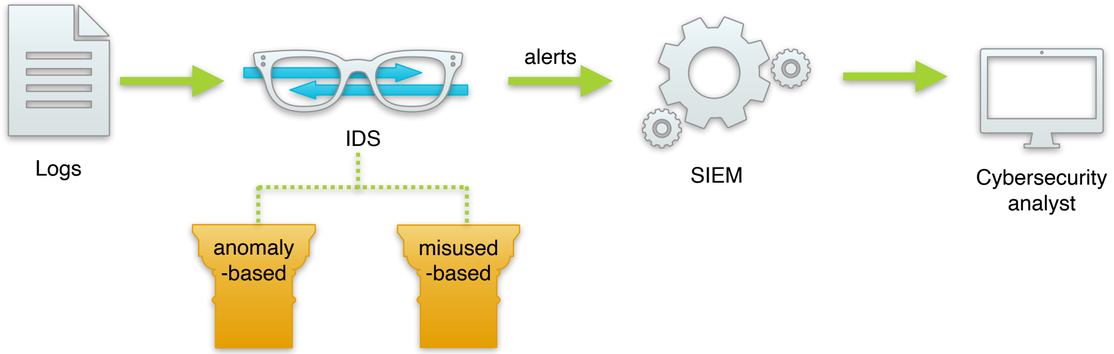
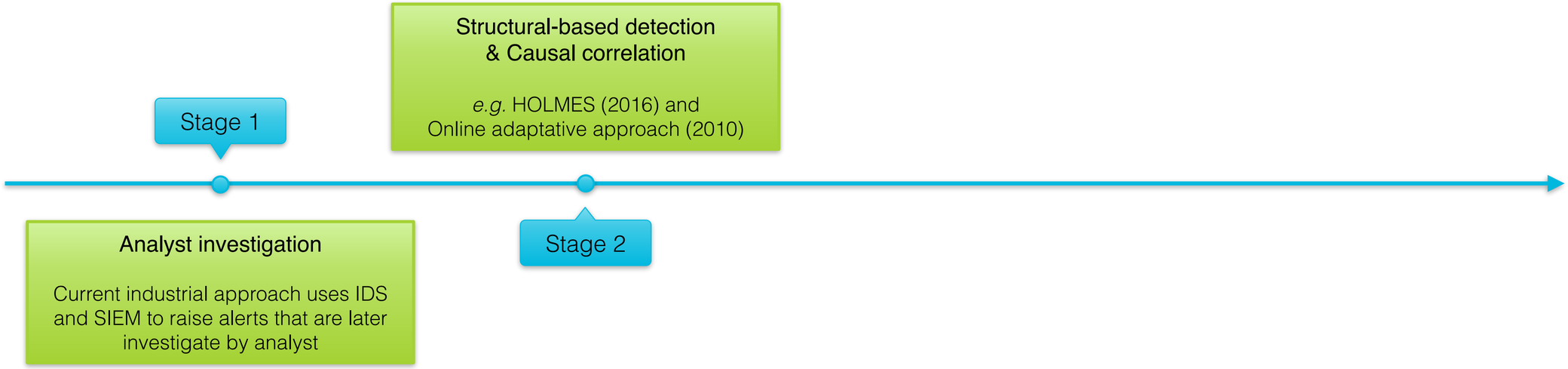
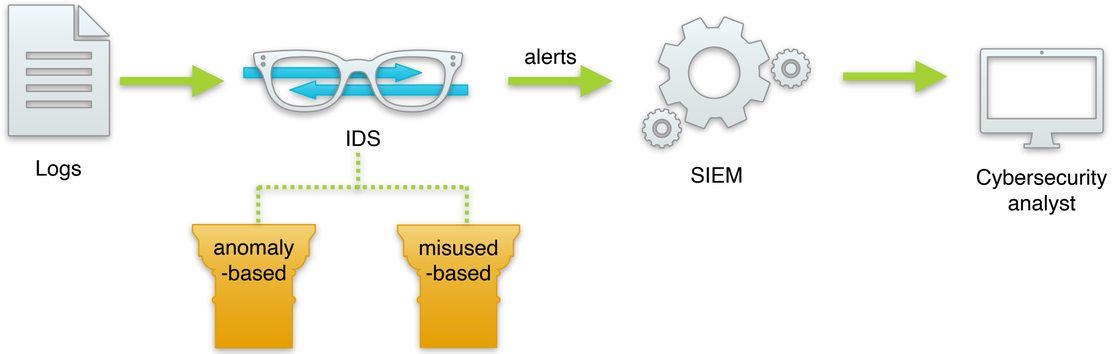


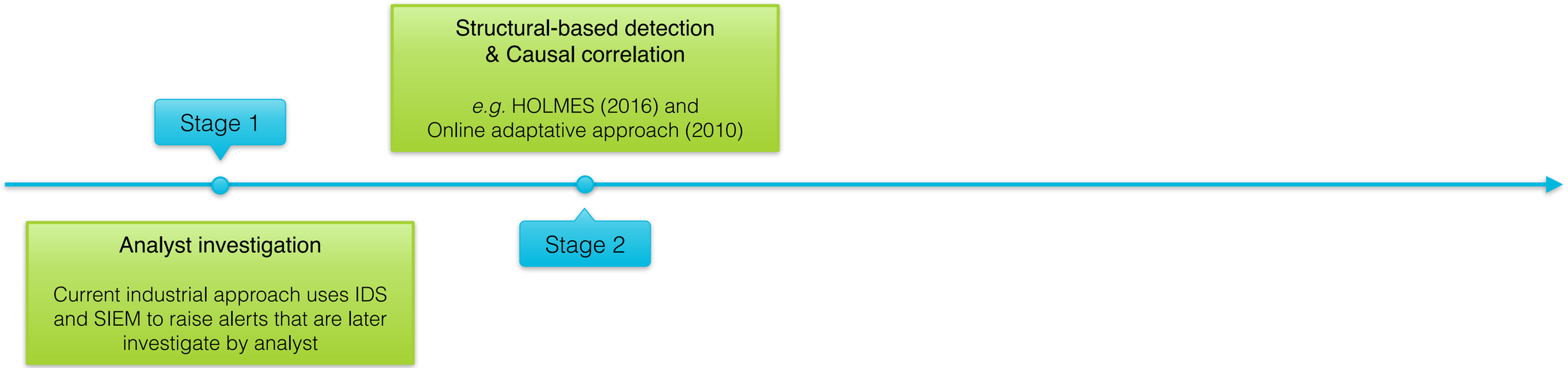
	Case-based	Structural-based
Human knowledge	✓	✓
Unknown attacks detection	✗	✗



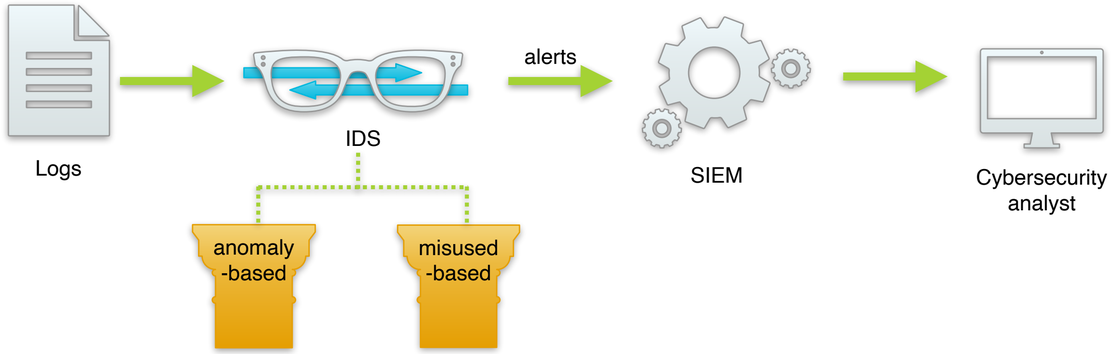
ON THE ROAD TO AUTOMATIC DETECTION



	Case-based	Structural-based	Causal correlation
Human knowledge	✓	✓	✗
Unknown attacks detection	✗	✗	Only light variations



ON THE ROAD TO AUTOMATIC DETECTION



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Human knowledge	✓	✓	✗
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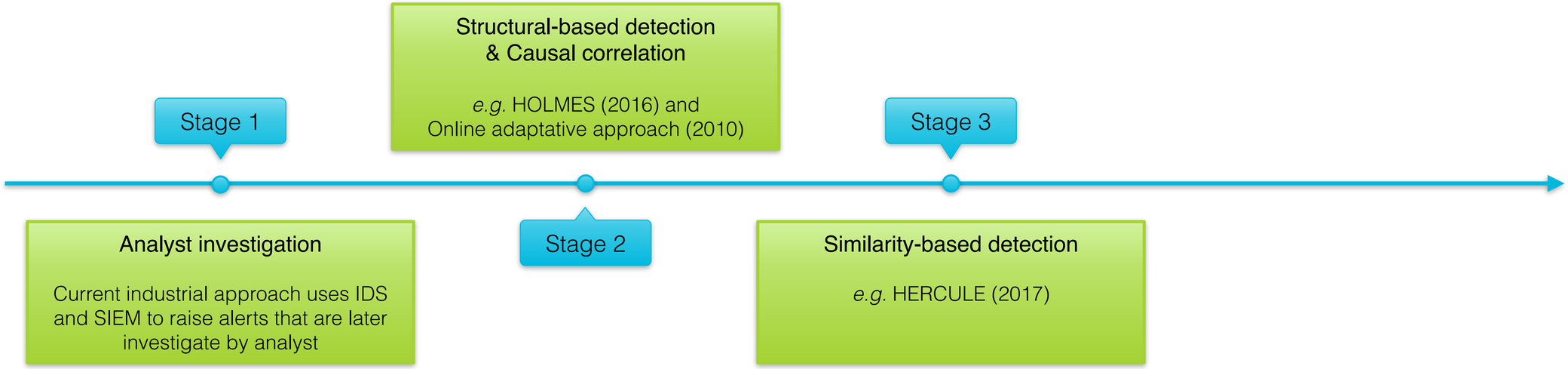
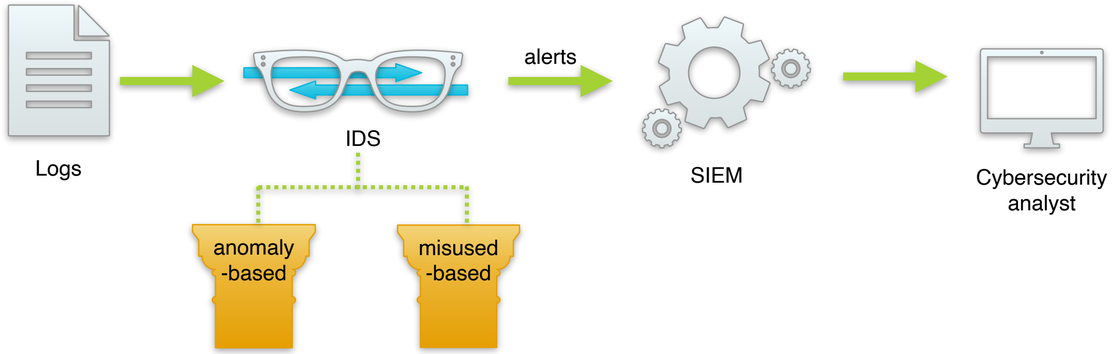
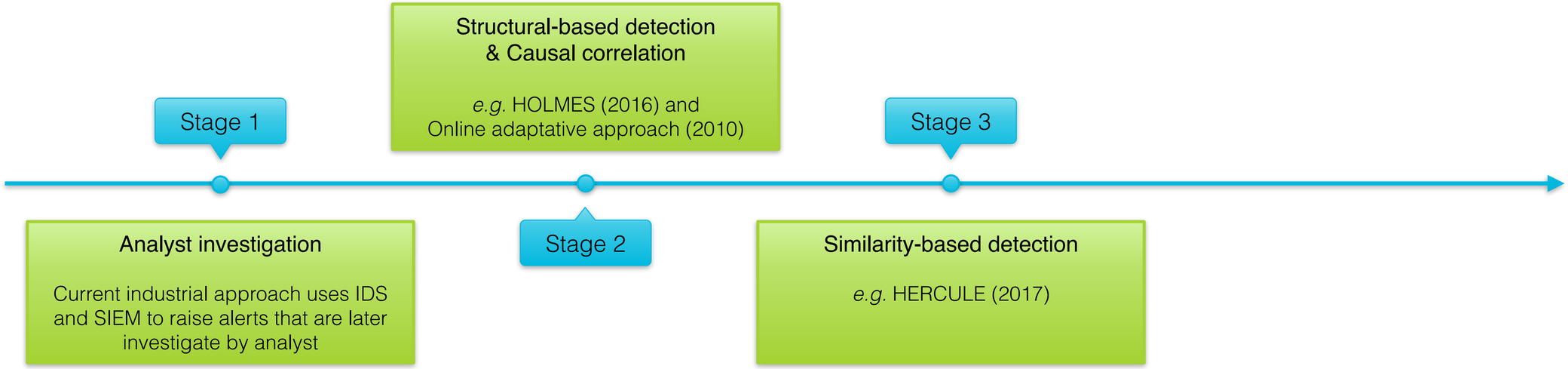


ON THE ROAD TO AUTOMATIC DETECTION



	Case-based	Structural-based	Causal correlation	Similarity-based
Human knowledge	✓	✓	✗	✗
Unknown attacks detection	✗	✗	Only light variations	✓



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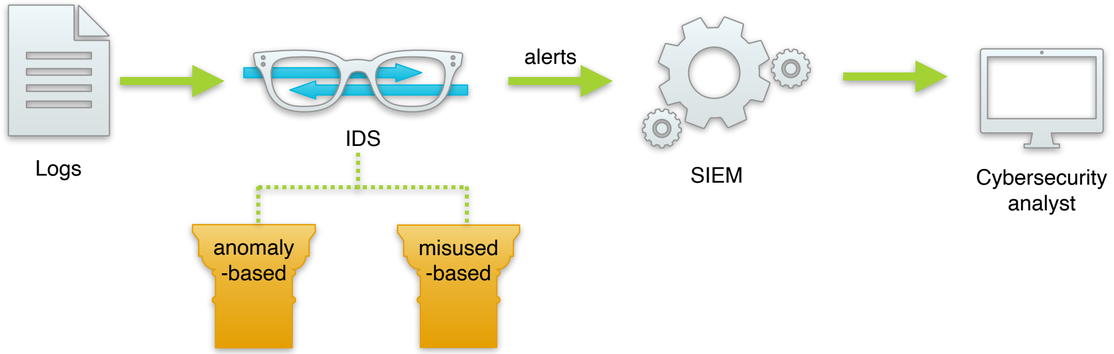
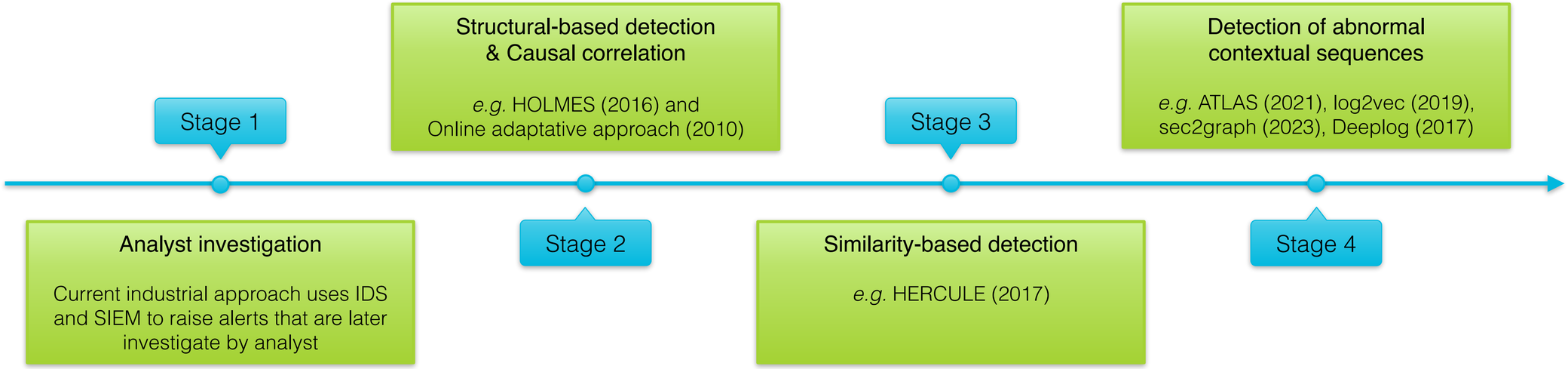
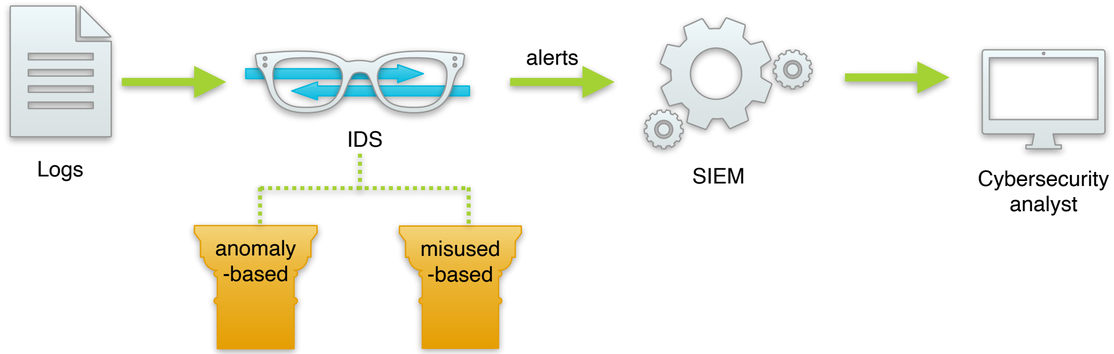


	Case-based	Structural-based	Causal correlation	Similarity-based
Human knowledge	✓	✓	✗	✗
Unknown attacks detection	✗	✗	Only light variations	✓



- **Decision support**
  - Sequences of contextual events
  - Highlight abnormal sequences of events
  - Reduce alert fatigue and detects discrete behaviors



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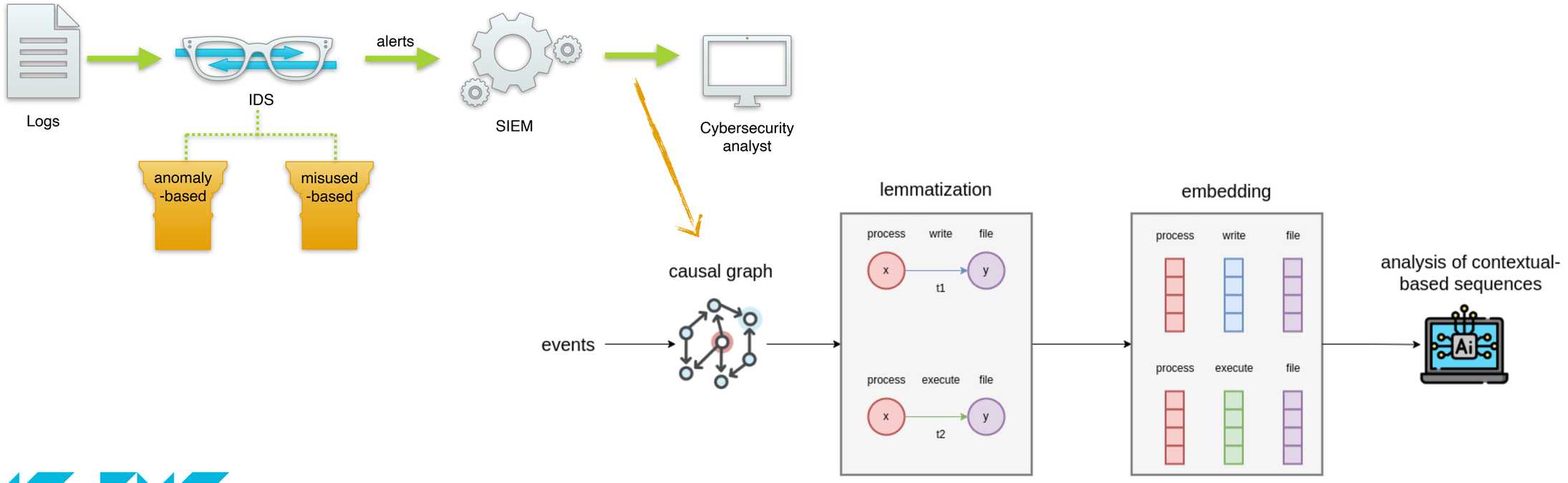

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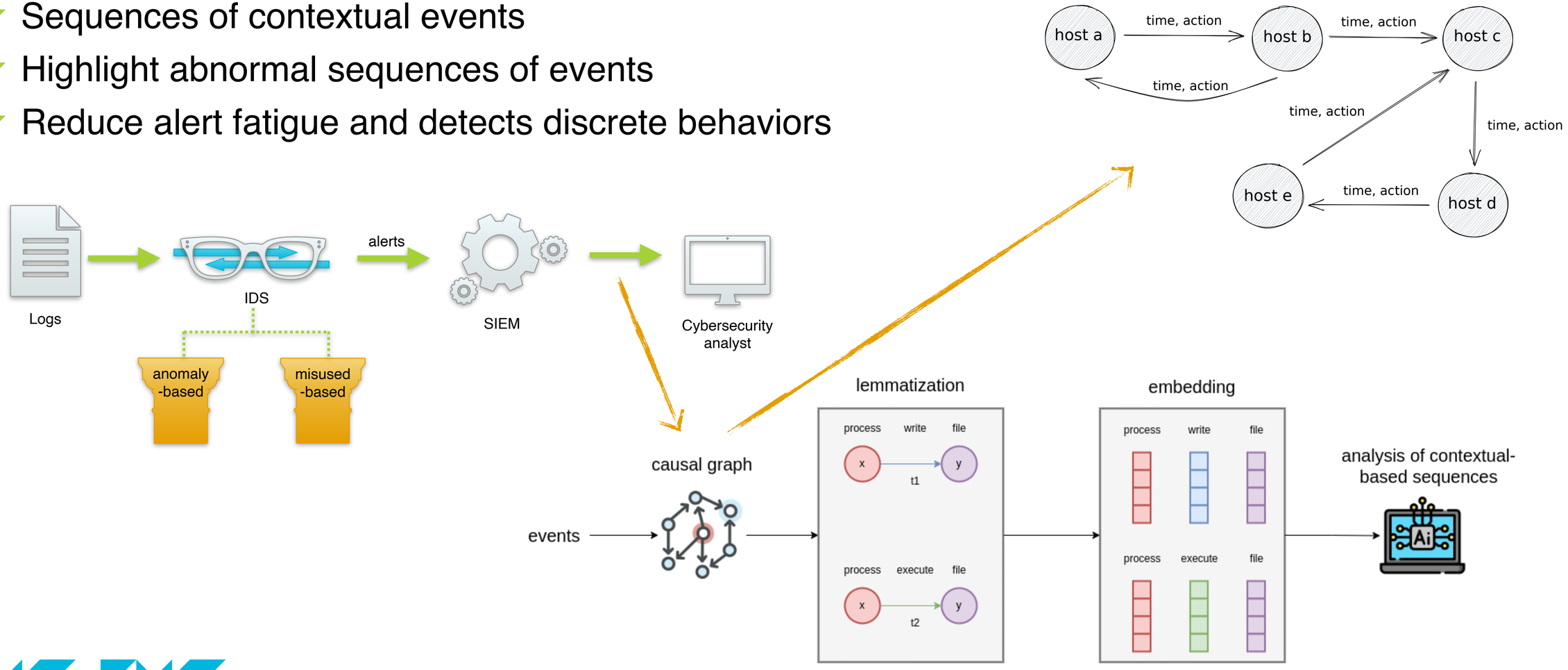


FEDERATED LEARNING APPROACHES FOR DEFENDING AND DETECTING CYBER-ATTACKS

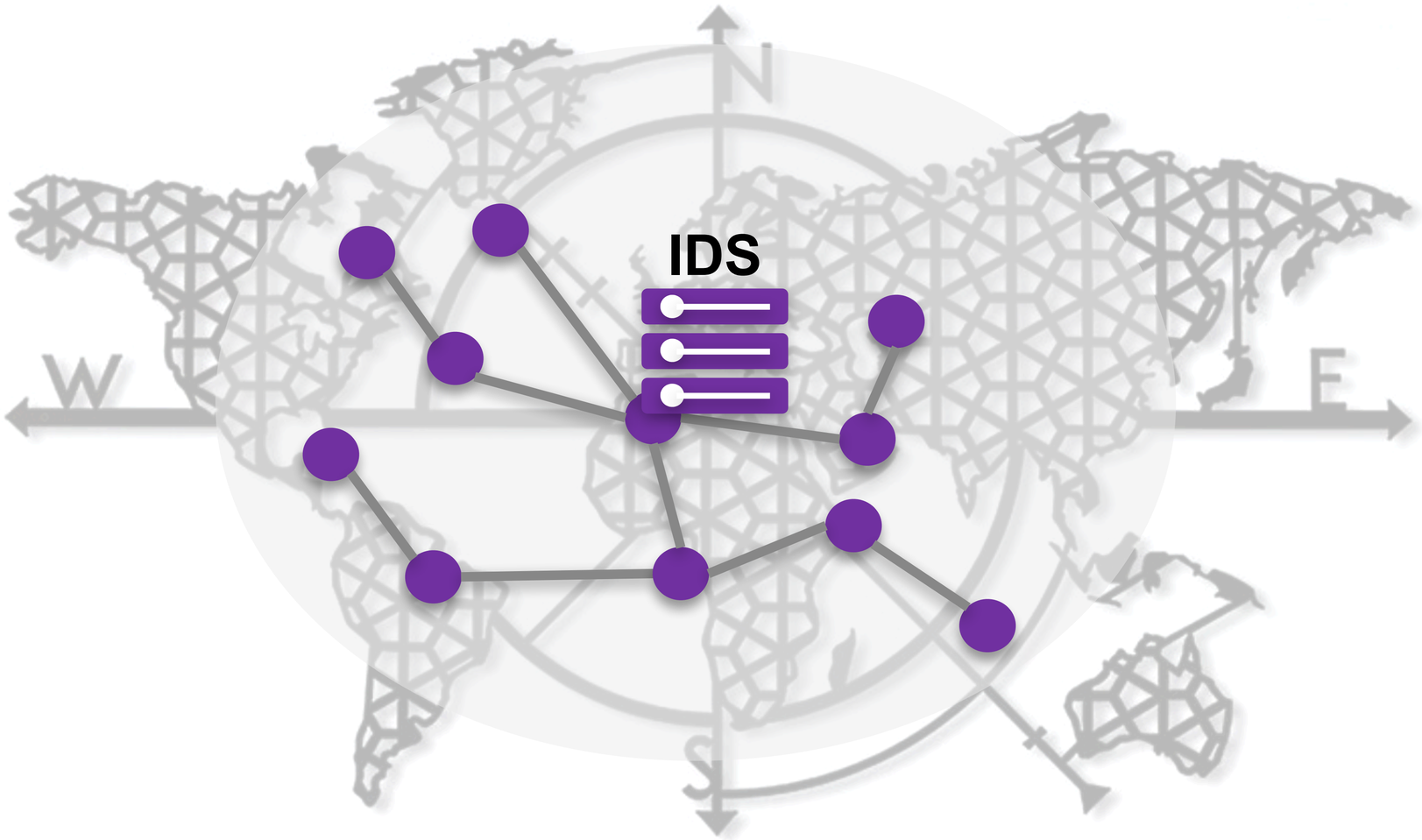
JOINT WORK WITH YANN BUSNEL (IMT NORD EUROPE)
LEO LAVAUR, FABIEN AUTREL, AND MARC-OLIVER PAHL (IMT ATLANTIQUE)

IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

SECURITY MONITORING

Cyberattack detection in infrastructures



IMT Atlantique
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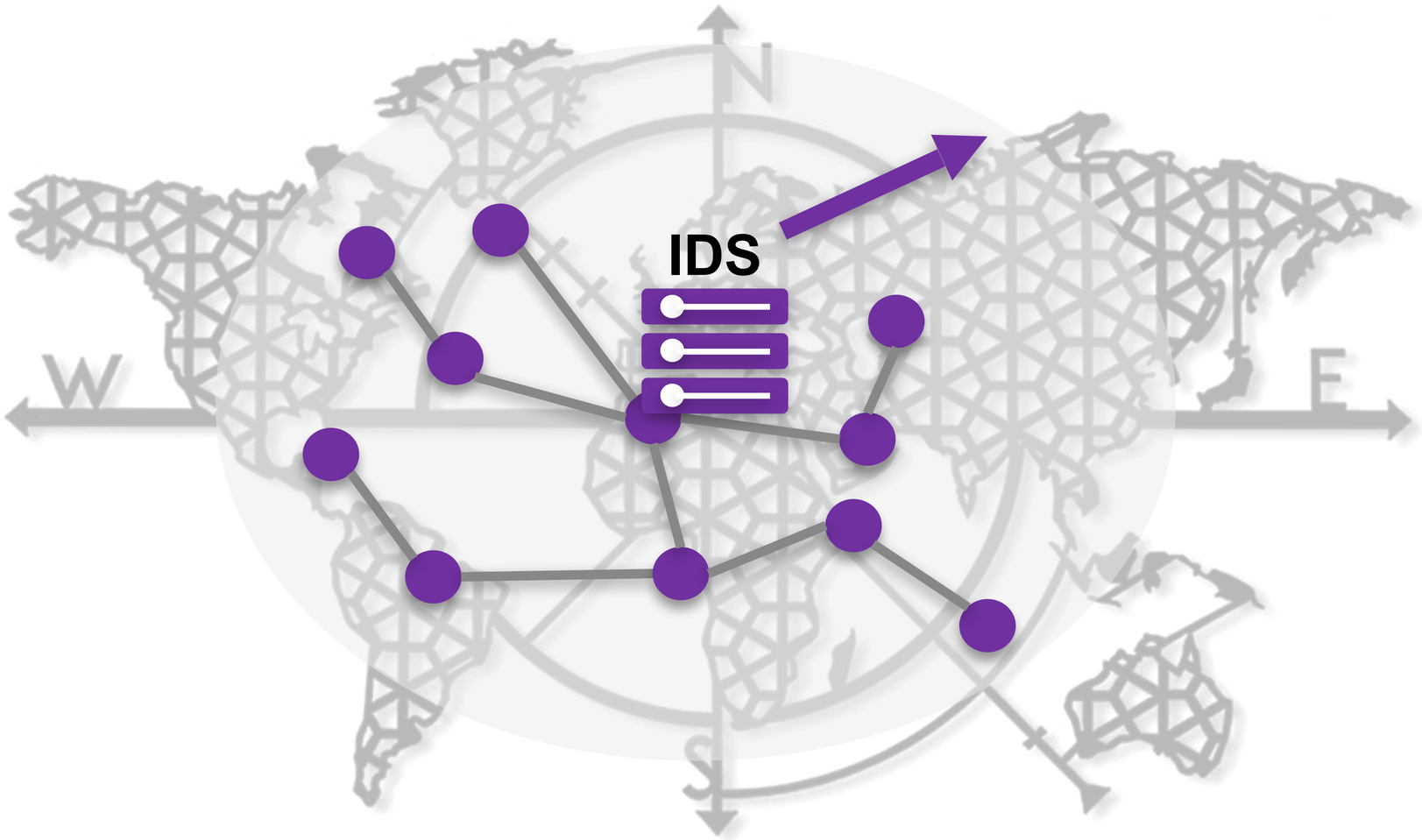
École Mines-Télécom

SECURITY MONITORING

Cyberattack detection in infrastructures



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SECURITY MONITORING

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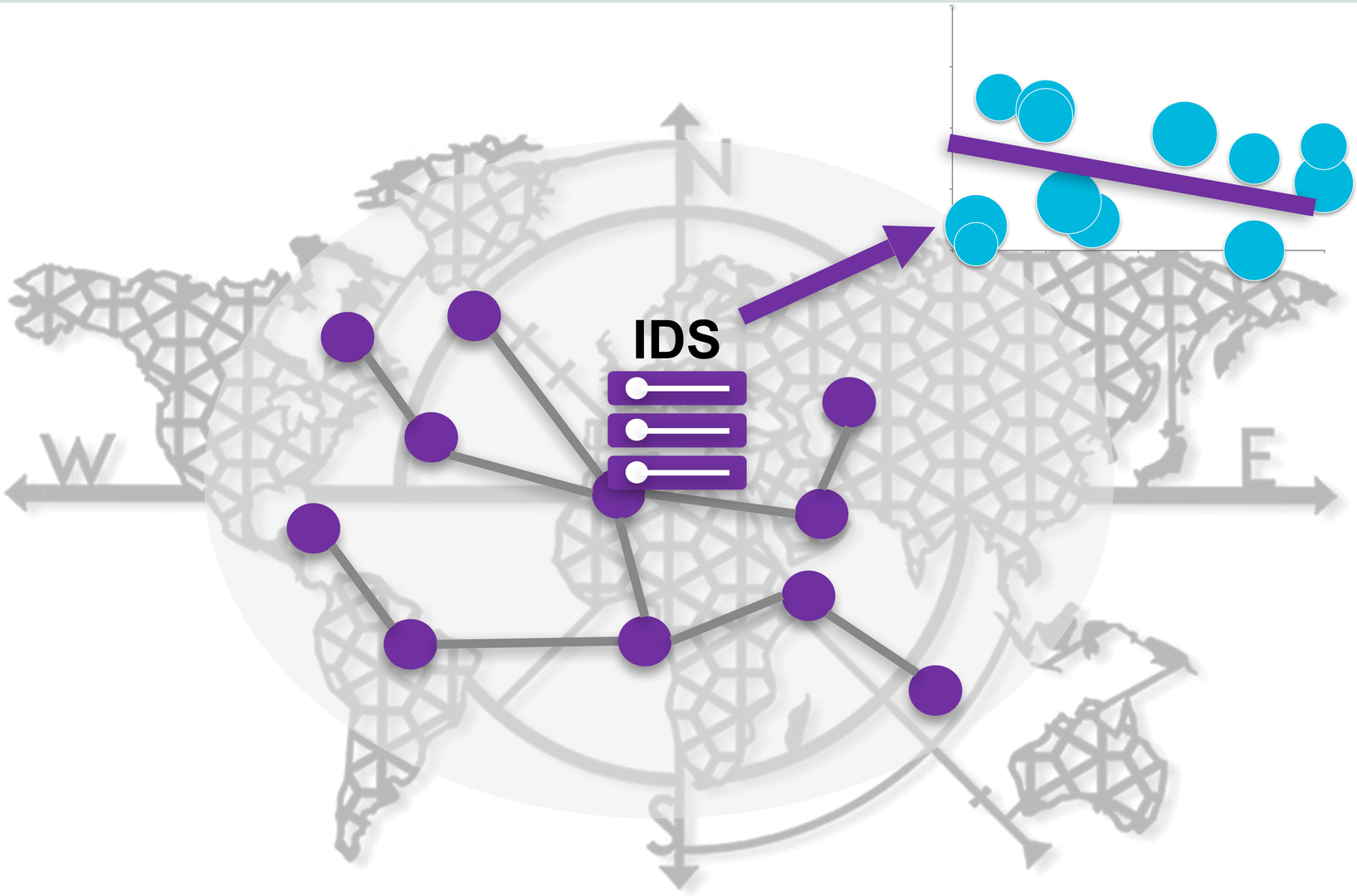

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SECURITY MONITORING

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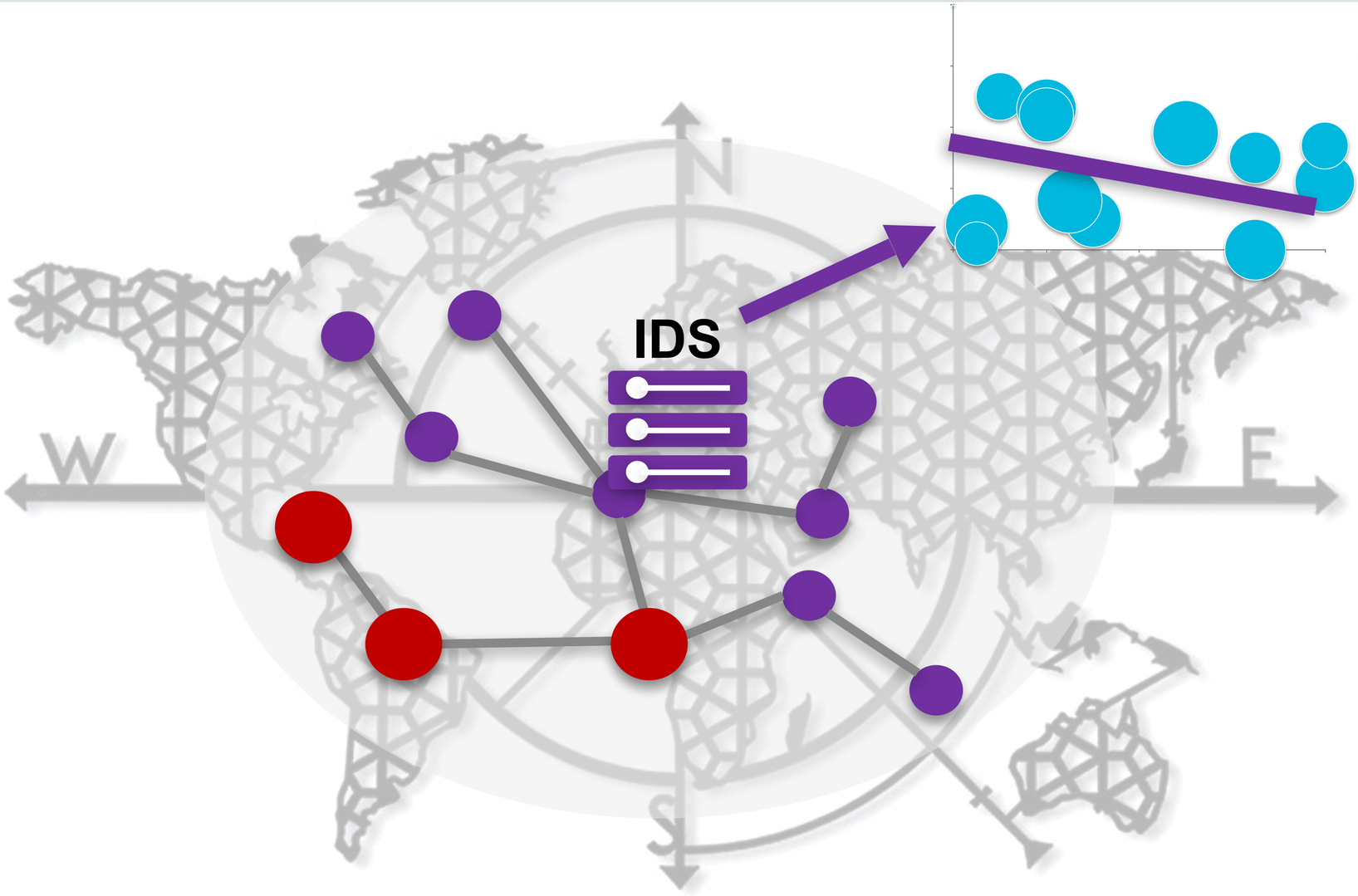
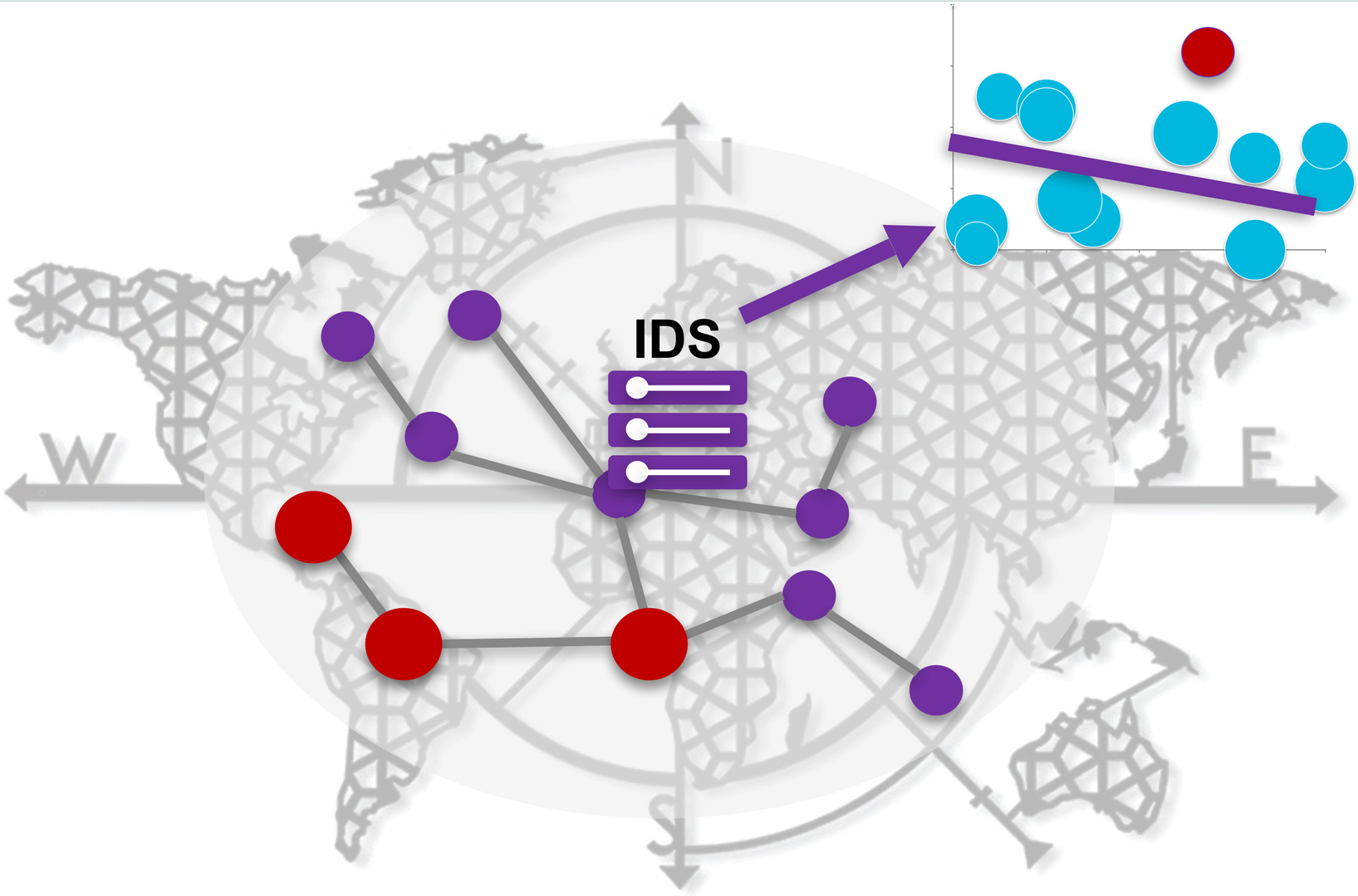


IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

SECURITY MONITORING

Cyberattack detection in infrastructures



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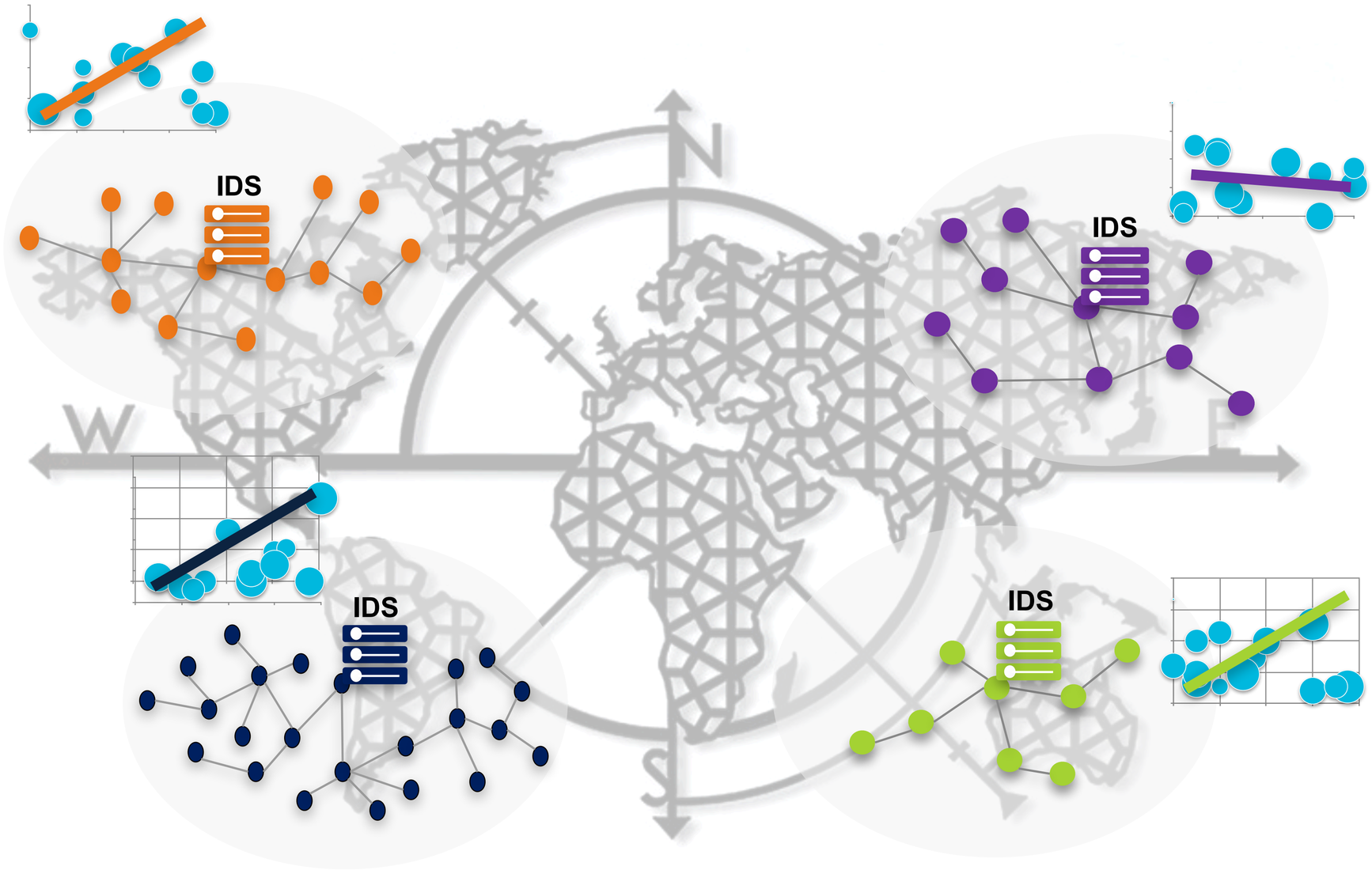
AT MULTIPLE ORGANISATION SCALE

How to share experience in intrusion detection?



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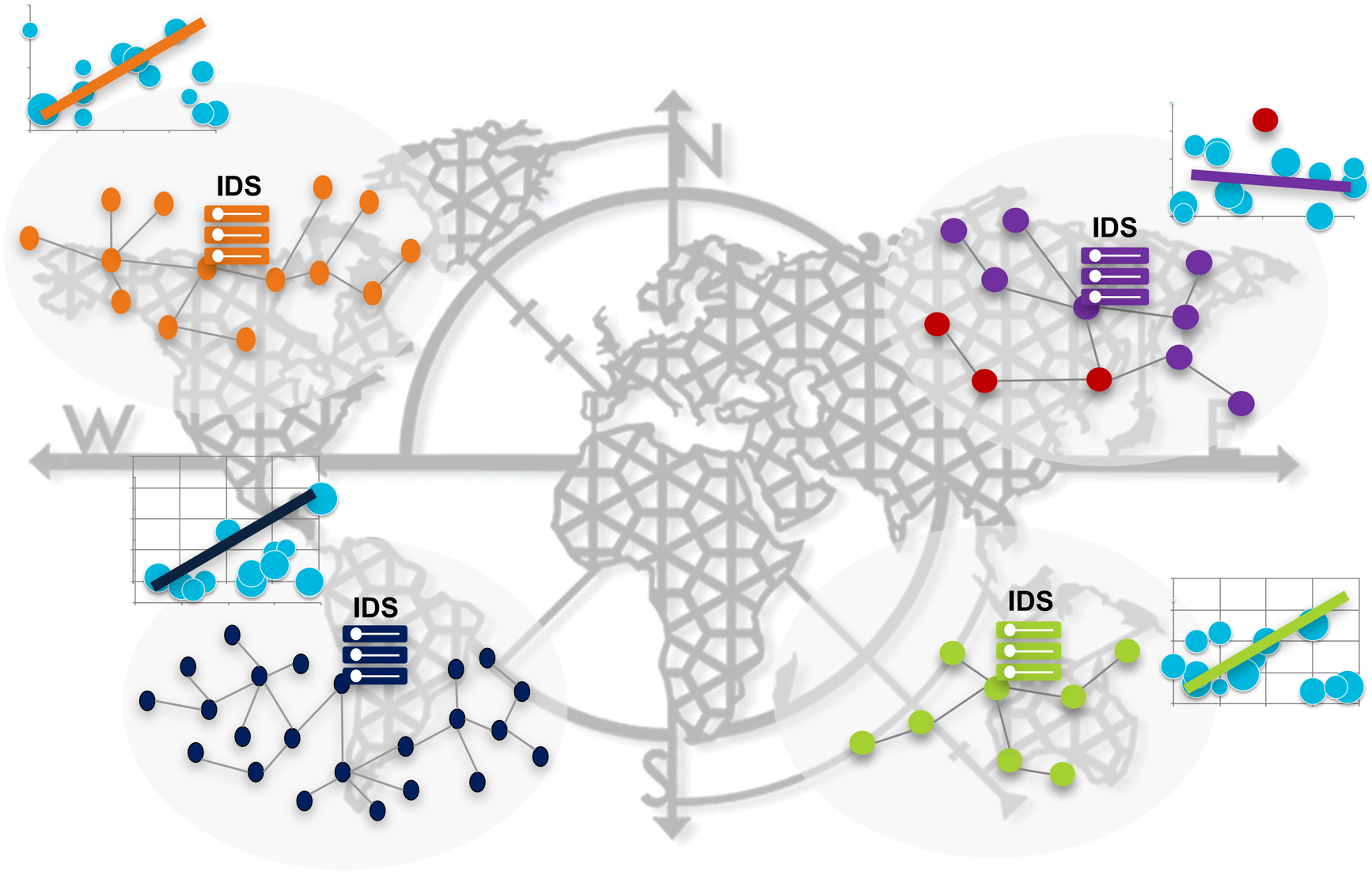

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AT MULTIPLE ORGANISATION SCALE

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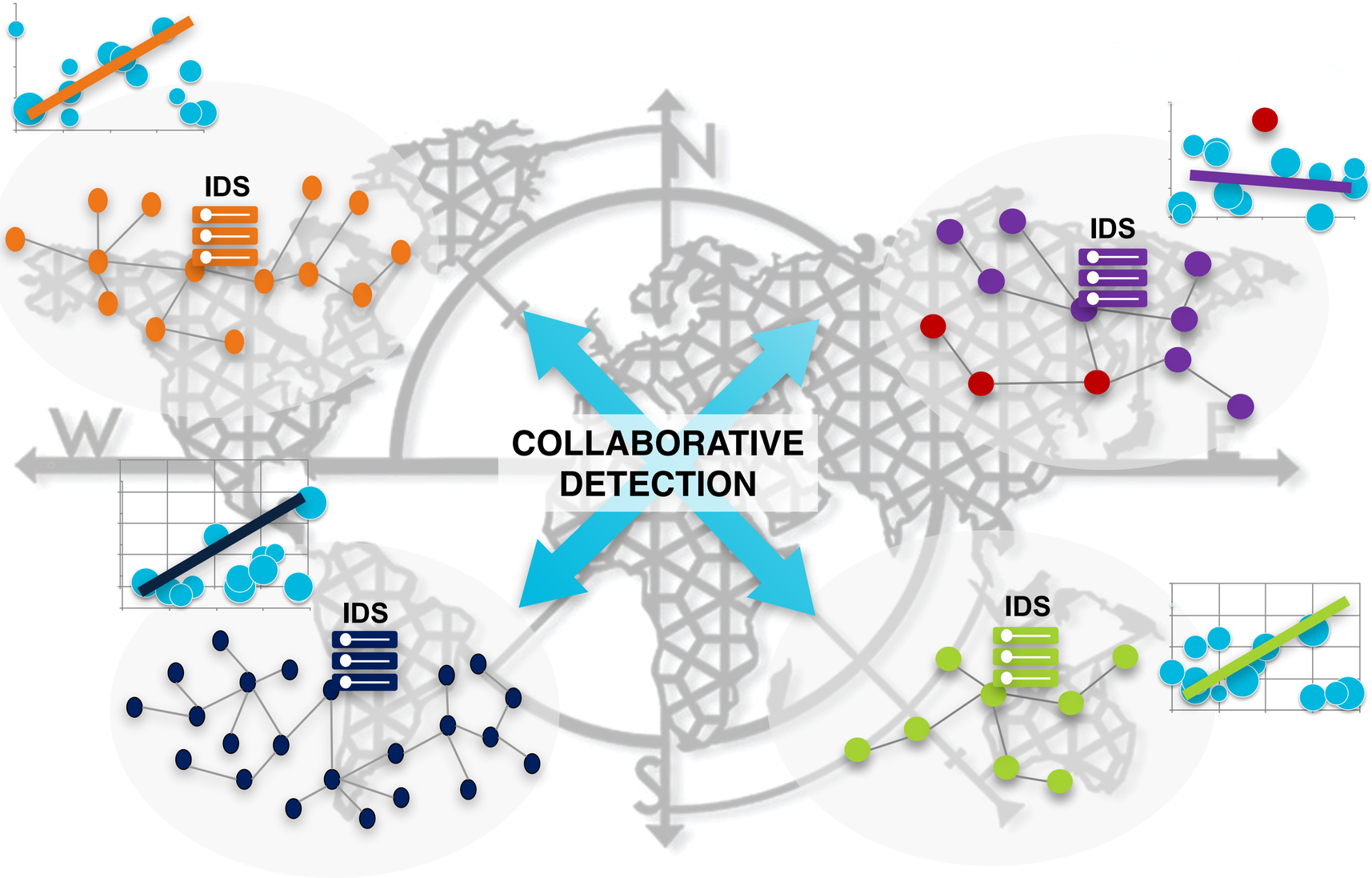

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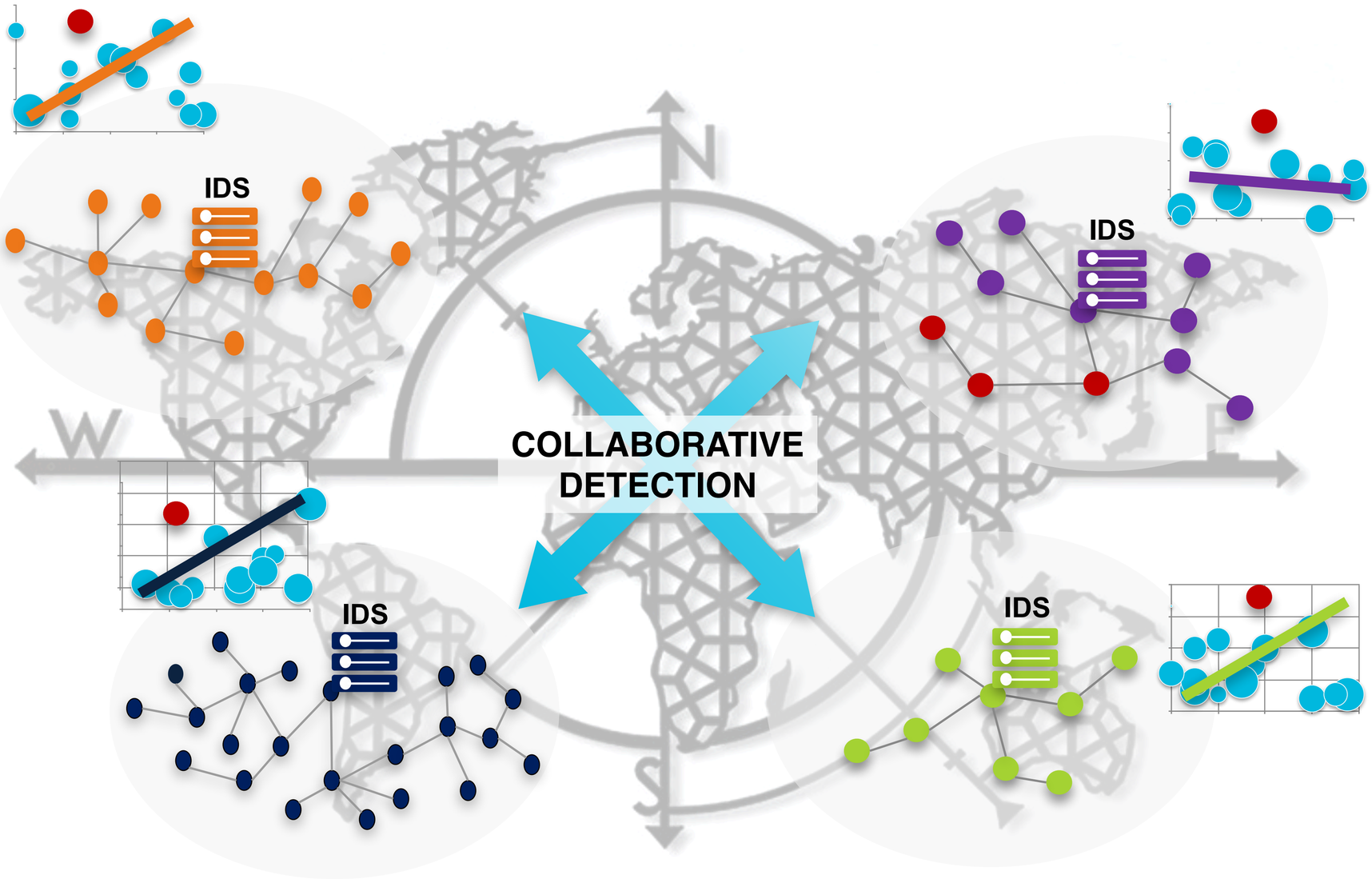

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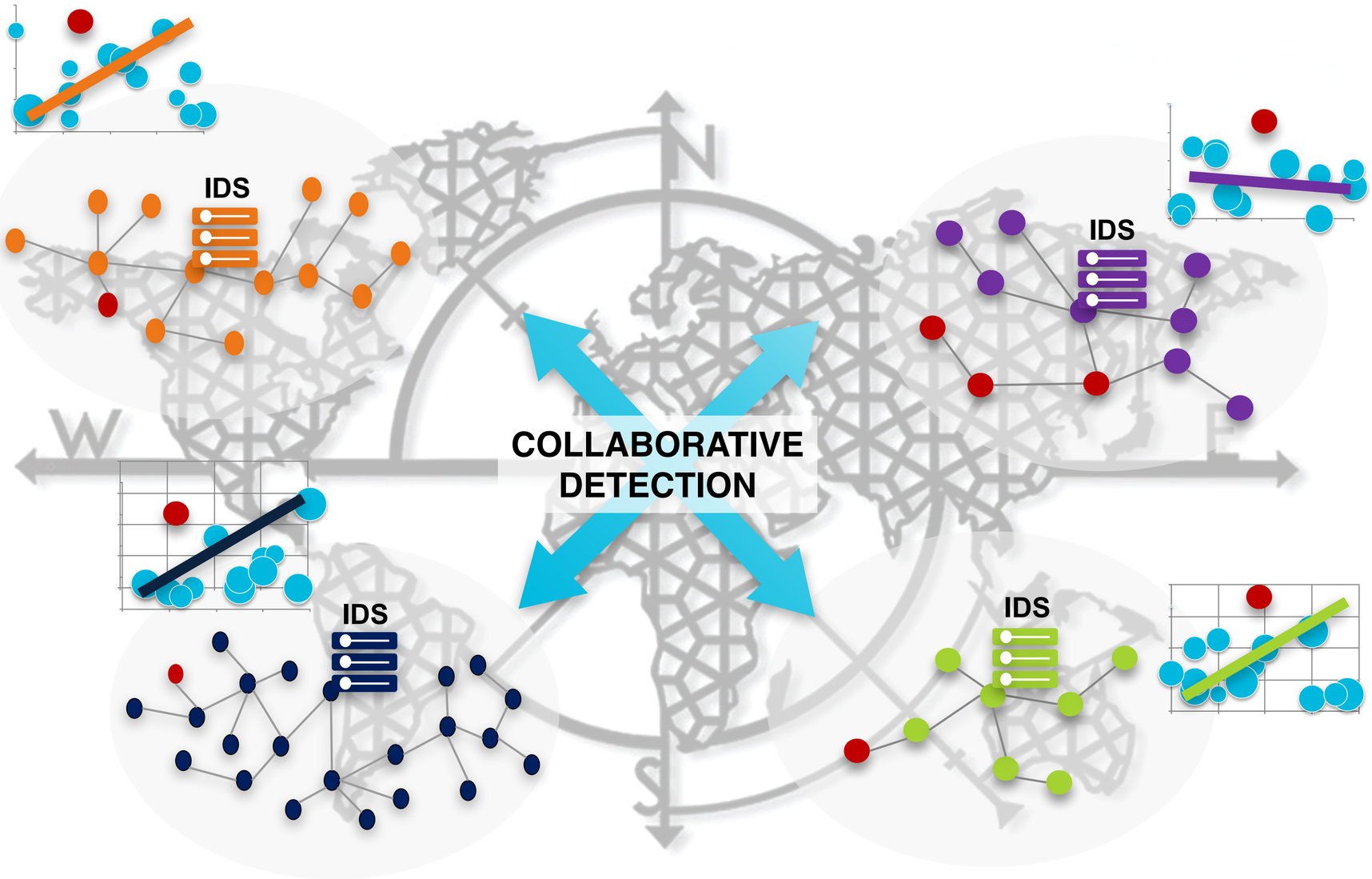

AT MULTIPLE ORGANISATION SCALE

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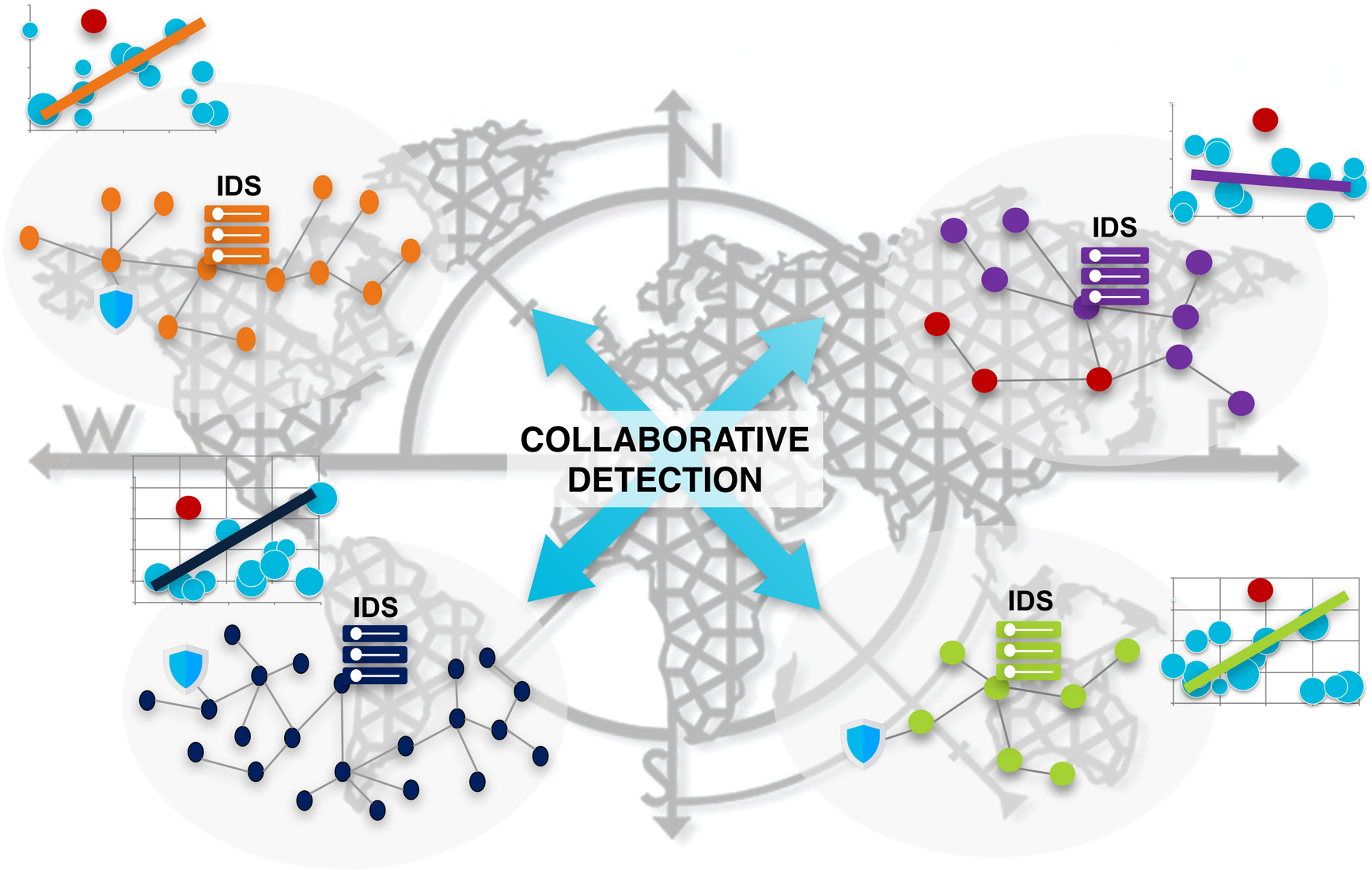
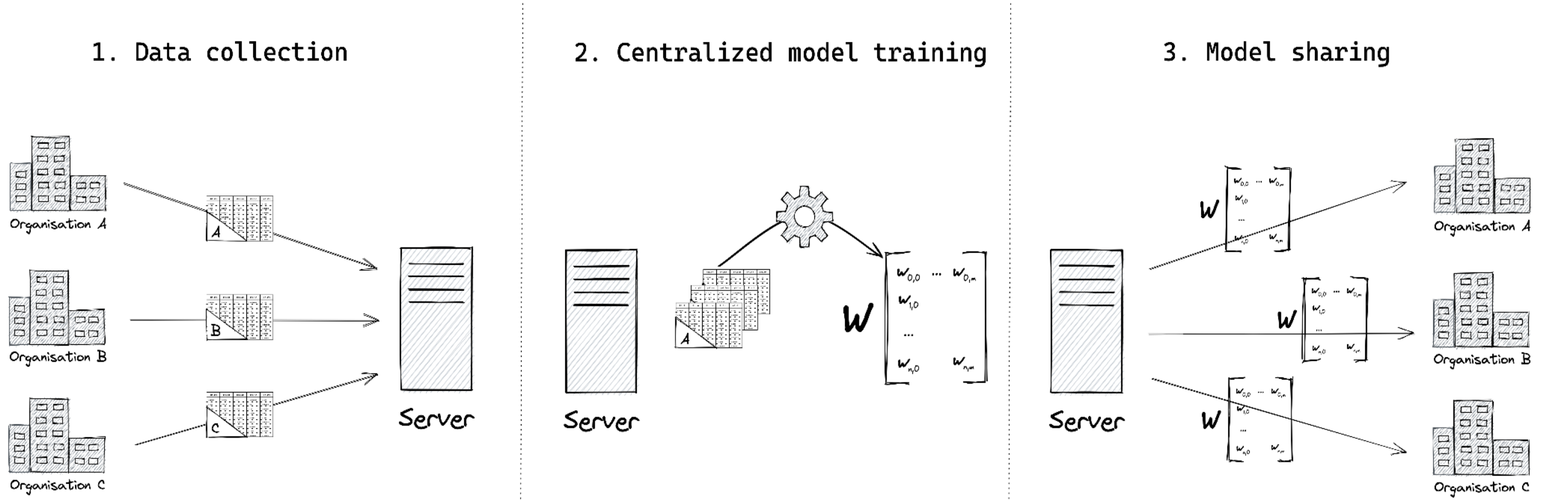


Collaborative Intrusion Detection

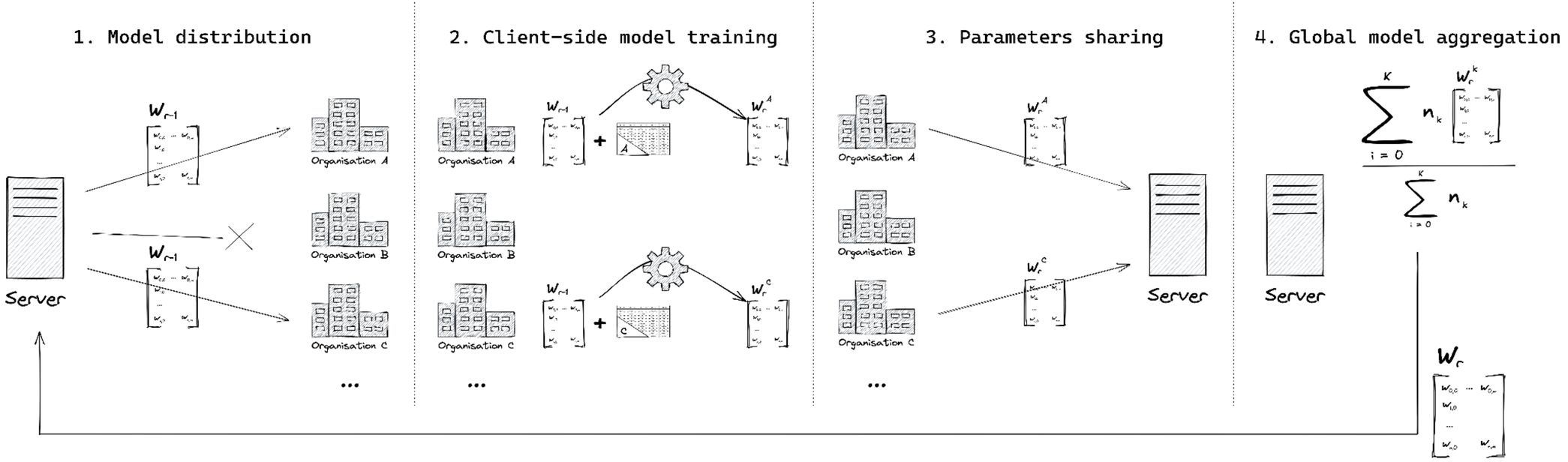
- **Objective**
  - Consolidate normal behavior modeling by sharing knowledge with other participants
- **Challenges**
  - Security & Privacy – *e.g.* revealing internals, poisoning, trust [1]
  - Availability – *e.g.* single point of failure in centralized systems [2]
  - Resources – *e.g.* high bandwidth consumption when sharing data [3]



[1] C. Fung et al. “Trust Management for Host-Based Collaborative Intrusion Detection.” In Managing Large-Scale Service Deployment, 2008.
[2] S. Rathore, et al., “BlockSecIoT-Net: Blockchain-based decentralized security architecture for IoT network,” Journal of Network and Computer Applications, 2019
[3] B. McMahan, et al., “Communication-efficient learning of deep networks from decentralized data”, 20th International conference on artificial intelligence and statistics, 2017

Federated Learning as a Collaborative Learning System

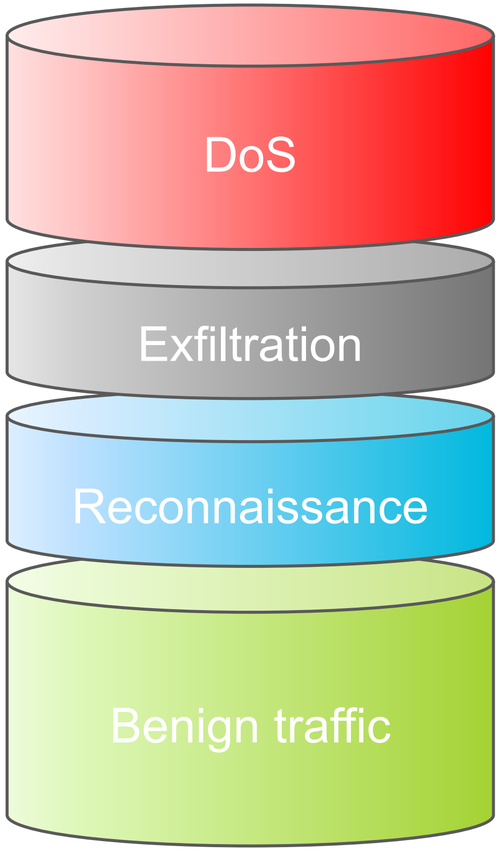
- **Challenges** [4]
  - Heterogeneity – unsuitable global aggregation when participants are too different
  - Trust – assessing peer contributions



[4] L. Lavaur, et al., "The Evolution of Federated Learning-Based Intrusion Detection and Mitigation: A Survey", IEEE Transactions on Network and Service Management, 2022

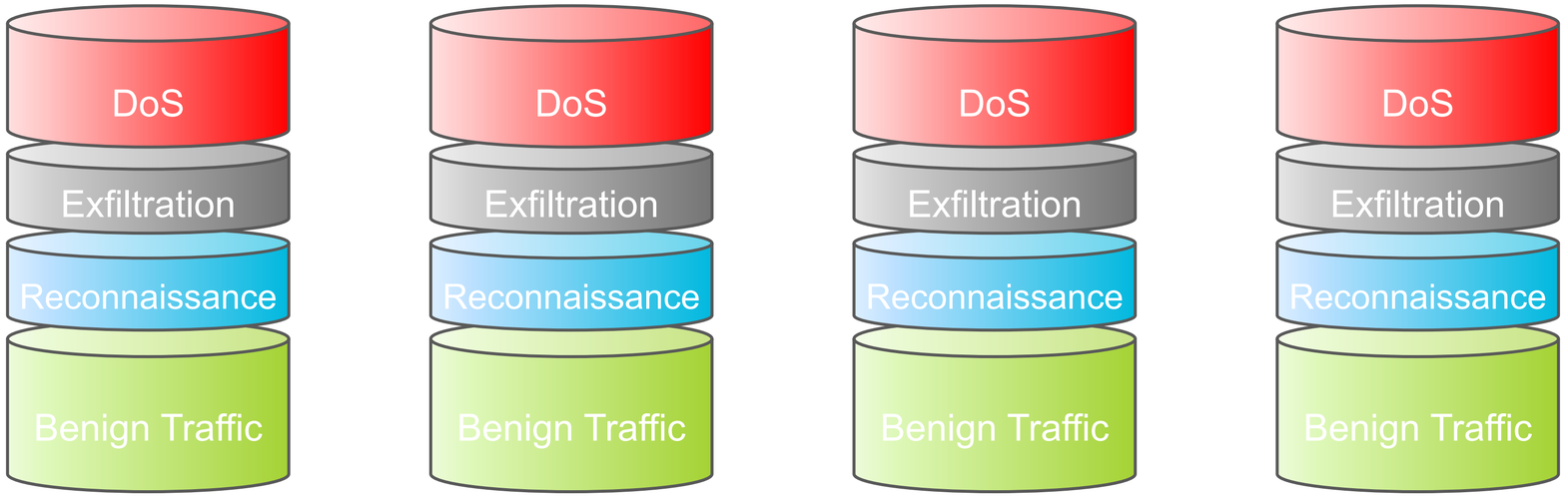
HOW TO DEAL WITH DATA HETEROGENEITY?

- **Classes of attack performed**
  - Denial of service
  - Reconnaissance (port scanning)
  - Data exfiltration, etc.
- **Trained algorithms**
  - Supervised learning on legitimate traffic and attacks
  - Neural networks: Multi-Layer Perceptron (MLP) type



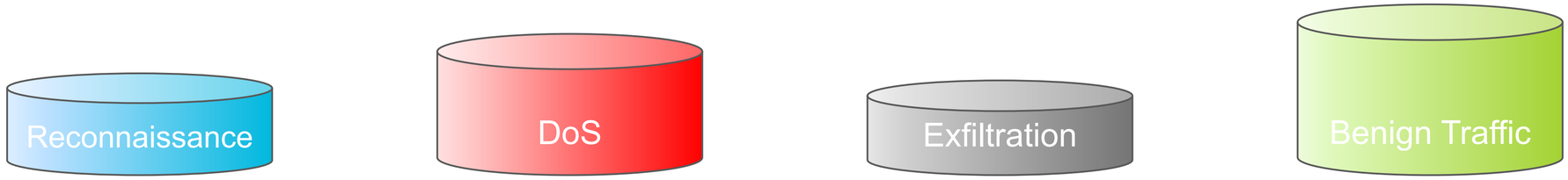
IDEAL CASE: FEDERATED LEARNING ON HOMOGENOUS DATA

- **Homogeneous distribution of the dataset over 4 sites**
  - IID data (Independently and Identically Distributed)
  - No overlap in samples (disjoint data)



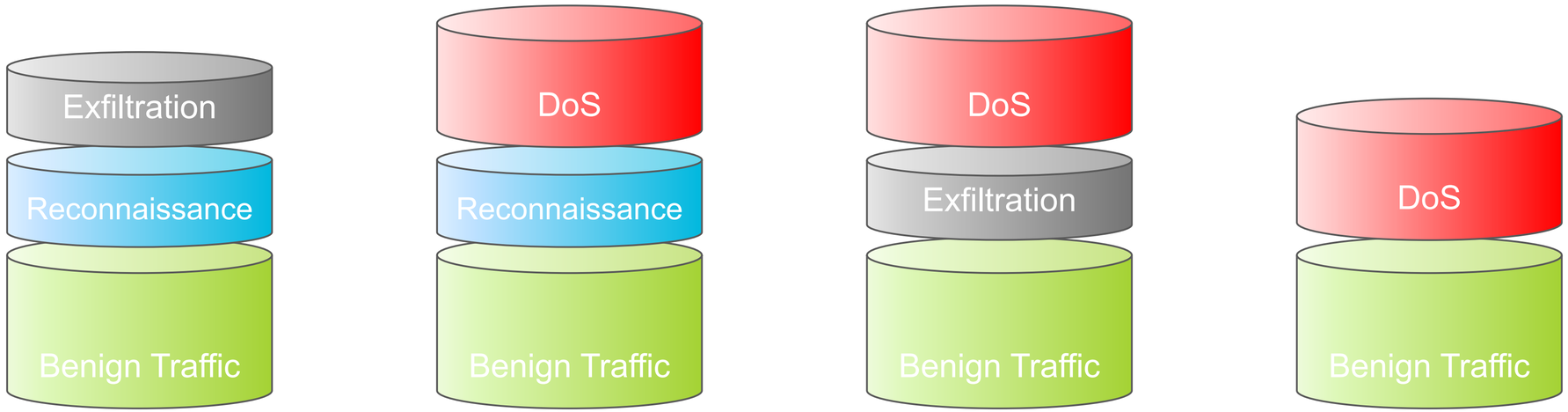
LESS IDEAL CASE: FEDERATED LEARNING ON HETEROGENOUS DATA

- **Differentiated distribution (NIID) of the dataset on 4 sites**
  - The data from the 4 sites do not contain the same attack classes
- **Pathological NIID [8]**
  - Only 1 class per client
  - Only 1 client per class
  - Not realistic in IDS context



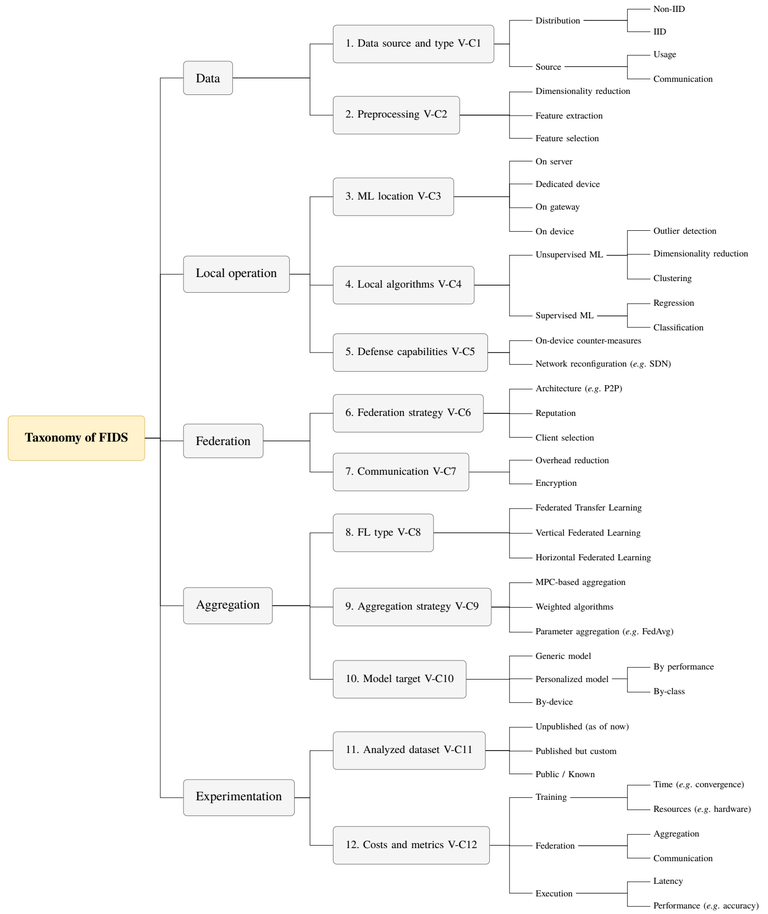
REALISTIC CASE: FEDERATED LEARNING ON HETEROGENOUS DATA

- **Differentiated distribution (NIID) of the dataset on 4 sites**
  - The data from the 4 sites do not contain the same attack classes
- **Practical NIID [8]**
  - Still no overlap in sample
  - Some classes can be shared by different clients, but usually not all



FIRST RECENT CONTRIBUTION ON FL

- **« The Evolution of FL-based intrusion detection and mitigation: a Survey »** [4]
  IEEE Transaction on Network and Services Management, 2022
  - Systematic Literature Review
  - Four contributions
    - Quantitative and qualitative structured analyses
    - Reference architecture
    - Taxonomy
    - Open issues and research directions



- **Research Open Questions answered by the survey**
  - How are FIDSs used in different domains?
  - What are the differences between FIDS architectures?
  - What is the state of the art of FIDSs?

[4] L. Lavaur, et al., “The Evolution of Federated Learning-Based Intrusion Detection and Mitigation: A Survey”, IEEE Transactions on Network and Service Management, 2022

OPEN ISSUES

1. Transferability, adaptability, and scalability [7], [9]-[14]

How to deal with high number of clients and constrained environments? How learn from heterogeneous data, or heterogeneous clients? How to balance generalization and specialization for models?

2. Security, trust, and resilience [9], [10], [14]-[16]

How to resist to poisoning and inference attacks against shared data? How to protect sharing and aggregation (HE, MPC, DP...)? How to deal with untrusted participants? How to mitigate attacks?

3. Algorithm and aggregation performance [5]-[8]

What is the impact of the hyper- and meta-parameters? How to model behaviors to better characterize traffic? How to improve the raw performance of models? What is the best data to train models.

HANDS-ON! — PART 2

FEDERATED LEARNING FOR SECURITY

SCAN ME

https://bit.ly/FLxSec-part2

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HOW TO SECURE THE FEDERATED LEARNING IN NETWORK MONITORING?

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ADVERSARIAL ATTACKS IN FEDERATED LEARNING

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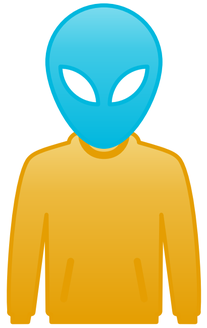
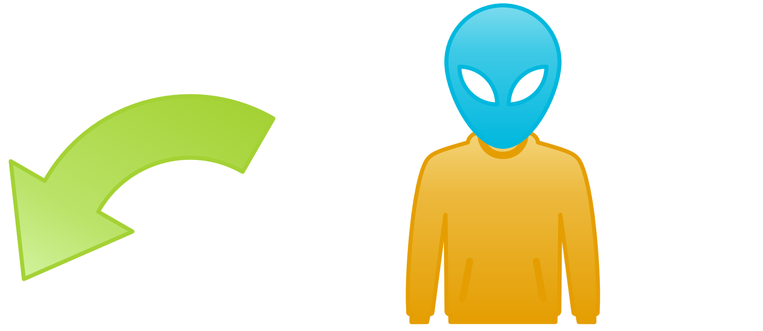


Adversarial attacks in federated learning

ADVERSARIAL ATTACKS IN FEDERATED LEARNING



Adversarial attacks in federated learning

Attacks to the federated model

- Aim at modifying its behaviour

ADVERSARIAL ATTACKS IN FEDERATED LEARNING

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Privacy attacks

- Aim at inferring sensitive information from learning

ADVERSARIAL ATTACKS IN FEDERATED LEARNING

Adversarial attacks in federated learning

Attacks to the federated model

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Privacy attacks

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- **Threat model**
  - Structured representation of information
    - Help to identify and define potential security issues
  - Defined in terms of
    - Information available
    - Scope of action of the attacker

Source: https://www.eccouncil.org/threat-modeling/

THREAT MODEL: INSIDER *VS.* OUTSIDER

- **Ousider**
  - Mainly focus on sniffing information of the communication channels between the involved agents
  - Aimed at **inferring information** about the data or the resulting learning model
- **Insider**
  - **More harmful**
  - Attack is carried out by one (or coalition) of the participants
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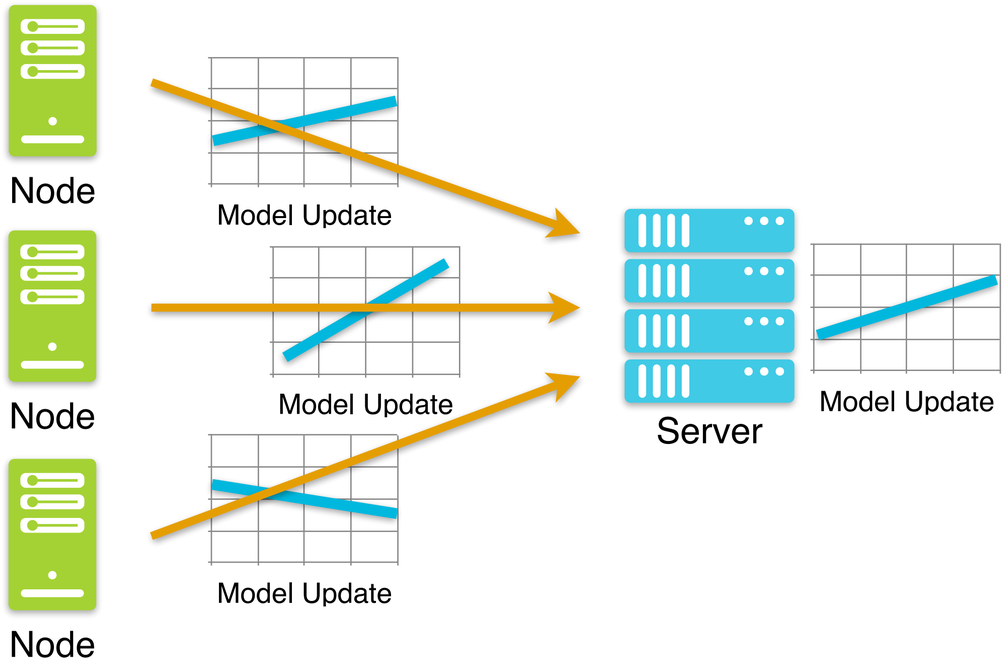

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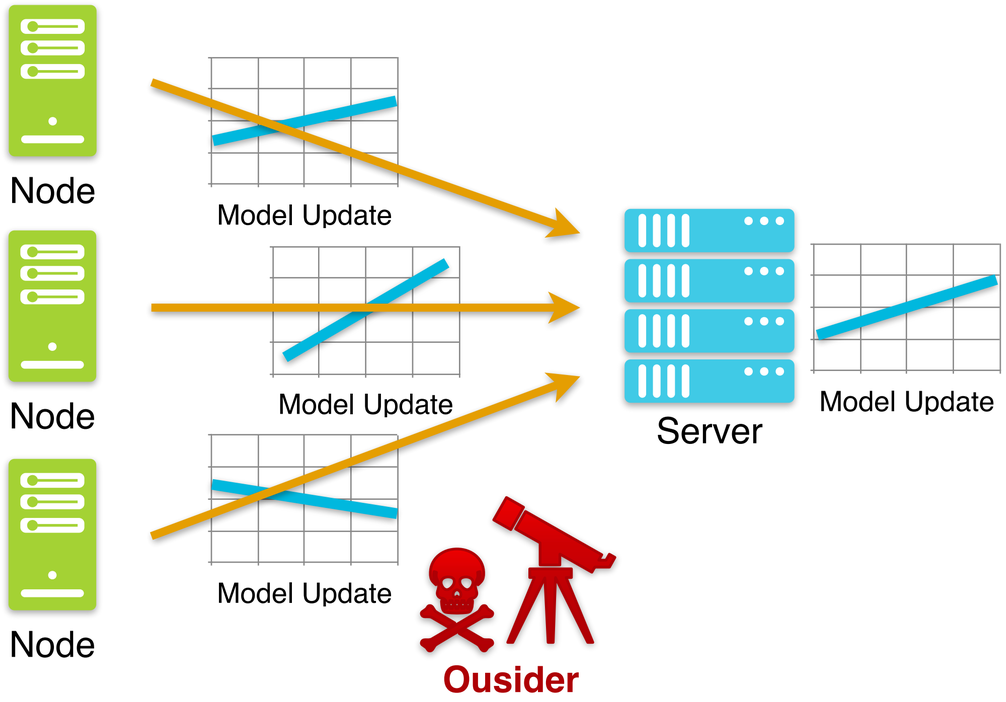

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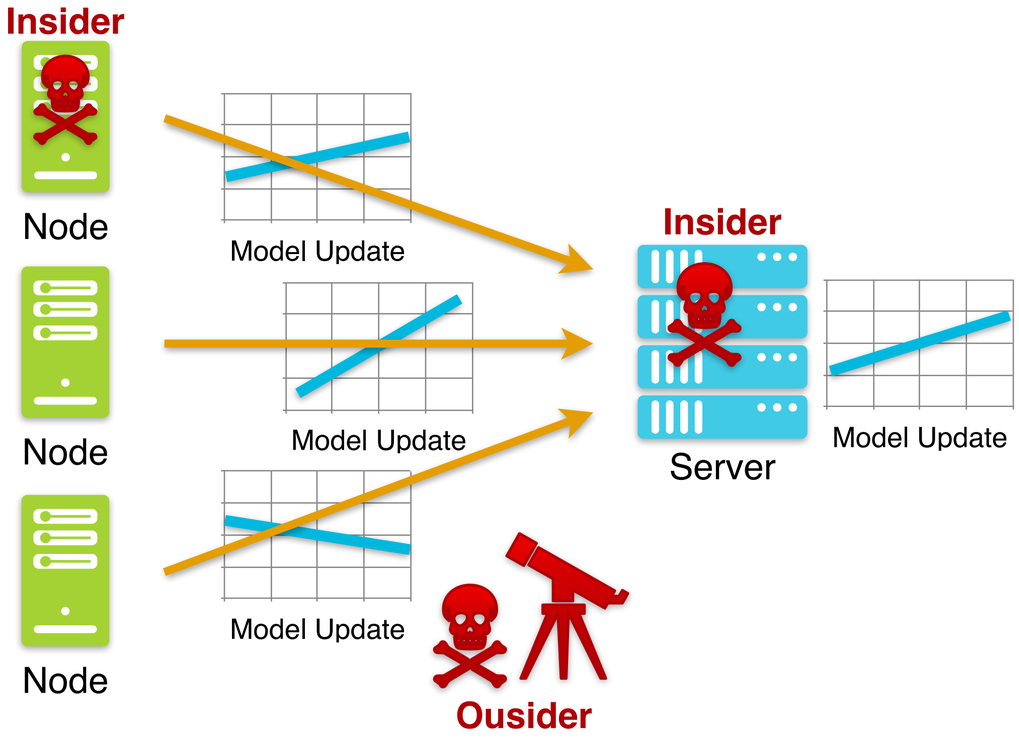
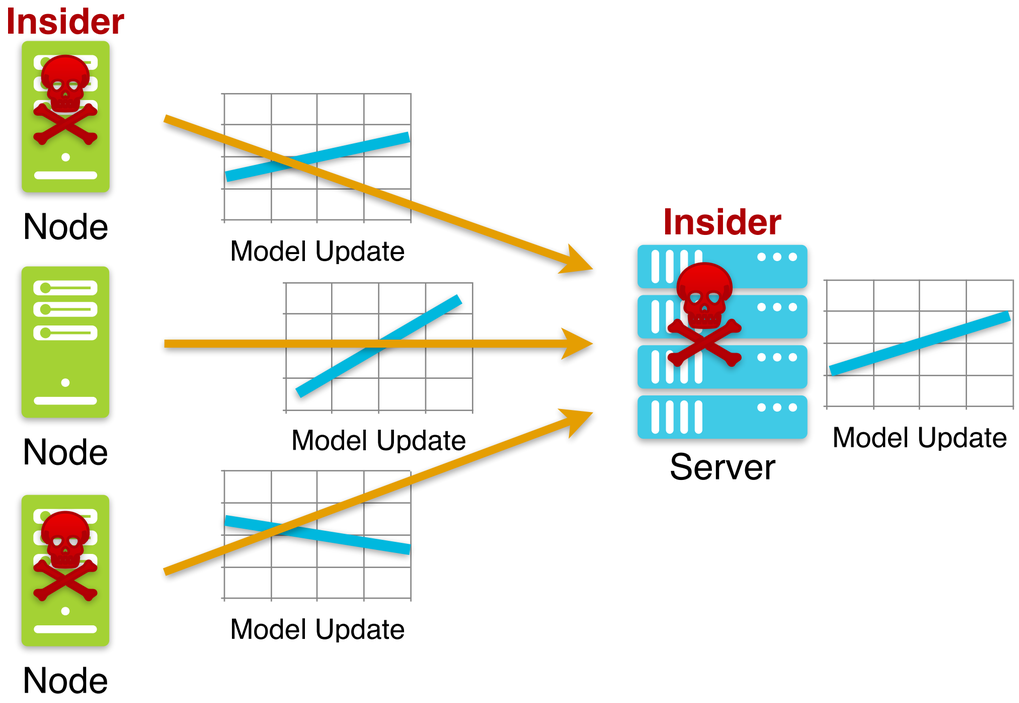


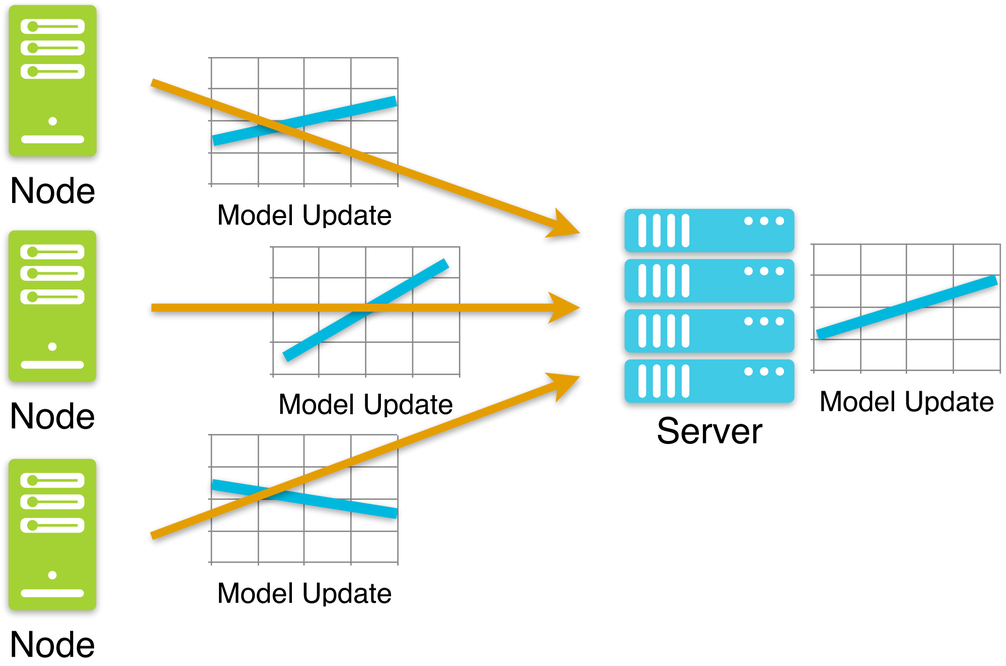
THREAT MODEL: FOCUS ON INSIDER CATEGORIZATION

- **Byzantine attacks**
  - Consist in sending arbitrary updates to the server
  - Aim to compromise the performance of the global learning model.
- **Sybil attacks**
  - Consist of collaborative attacks
    - By several attackers joining together
    - By simulating fictitious clients in order to be more disruptive
- **Honest-but-curious vs. Malicious**



OTHER THREAT MODEL TERMS

- **Client *vs.* Server**
- **Attacker knowledge**
  - Client-side knowledge *(sharing features & labels)*
    - Access to local data of other clients or their labels: Extra client-side knowledge
  - Server-side knowledge
  - Party-side knowledge *(sharing samples only)*
    - Access to information related to the features of the other clients: Extra party-side knowledge
  - Third party-side knowledge
  - Outsider-side knowledge
- **Collusion *vs.* No-collusion**



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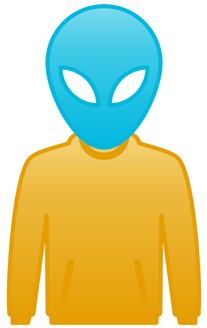
ADVERSARIAL ATTACKS TO THE FEDERATED MODEL

- **Clients have the ability to harm the model by sending poisoned updates**
  - The server cannot inspect the training data stored on the clients

4 TAXONOMIES OF ATTACKS [2]



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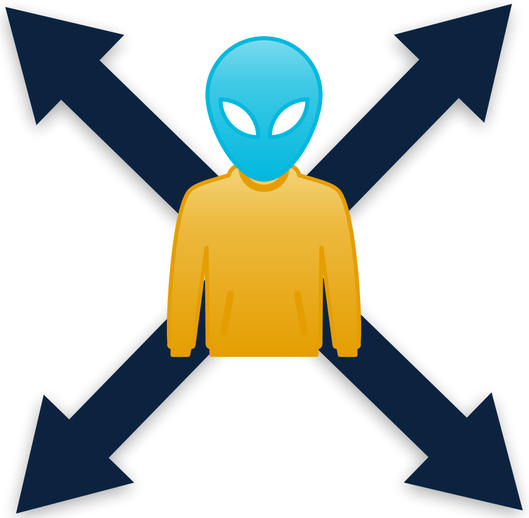
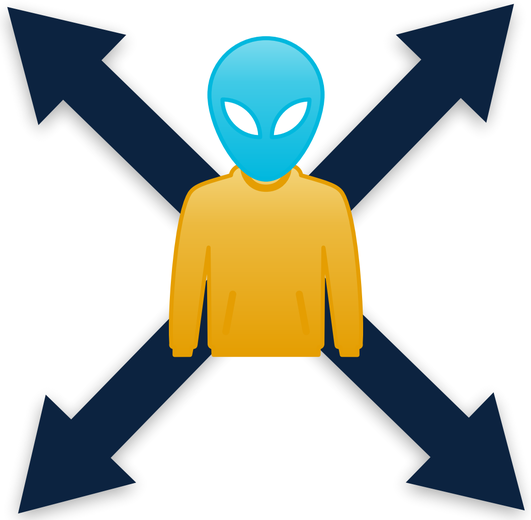


4 TAXONOMIES OF ATTACKS [2]

Attack moment

- Training time attacks
- Inference time attacks



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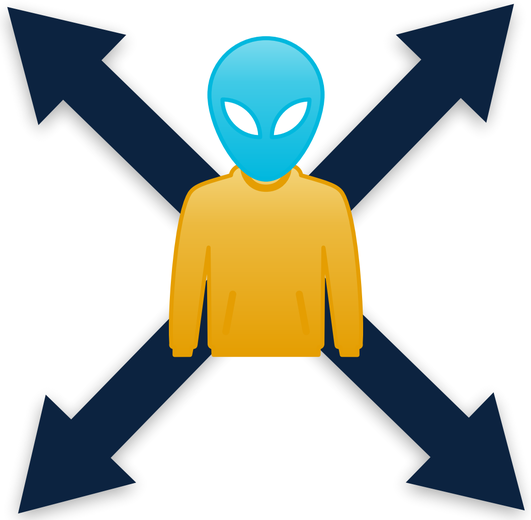

Objective

- Untargeted attacks
- Targeted/backdoor attacks

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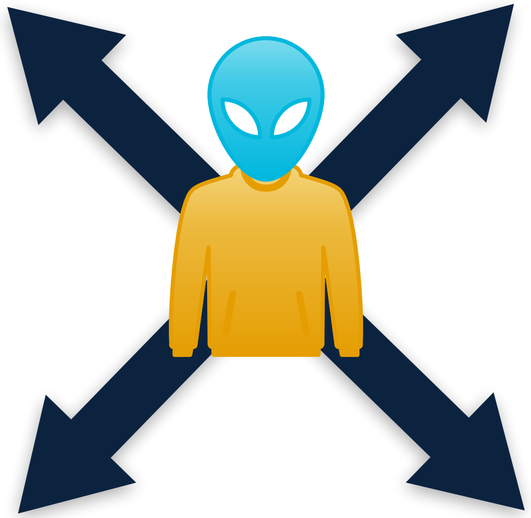
Poisoned part

- Data-poisoning attacks
- Model-poisoning attacks



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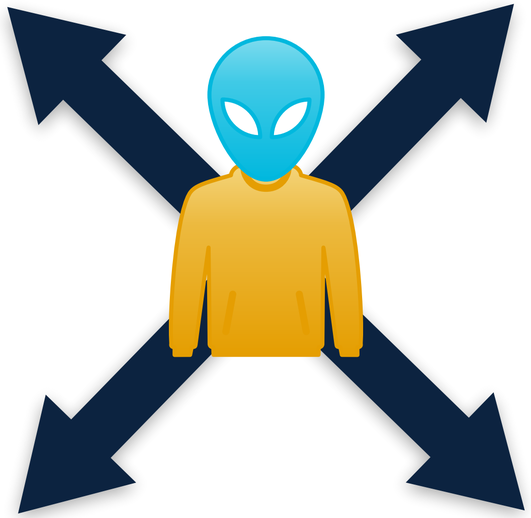

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Frequency

- One-shot attack
- Multiple or adaptive attack

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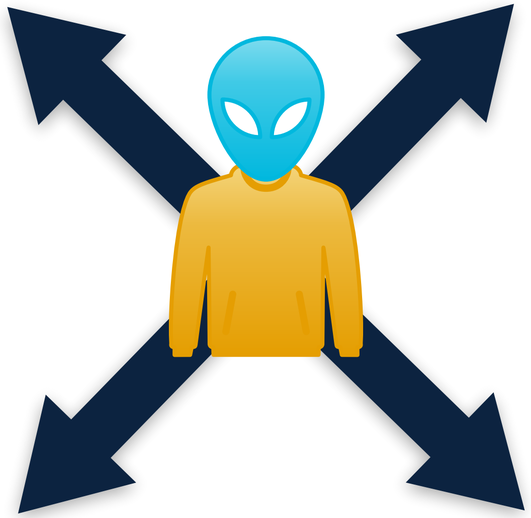

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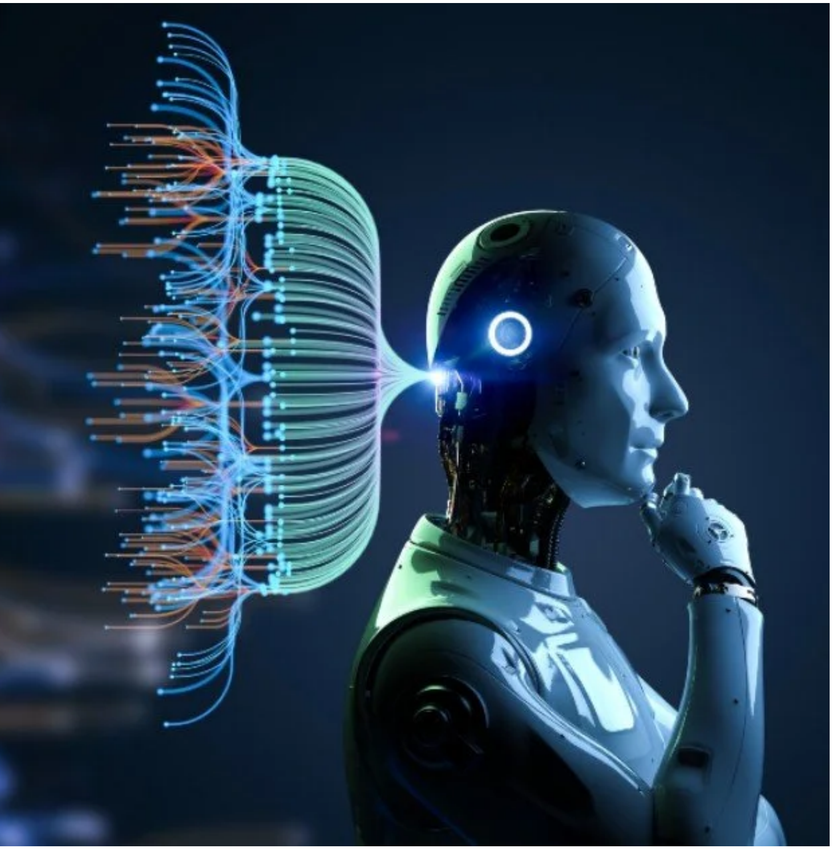
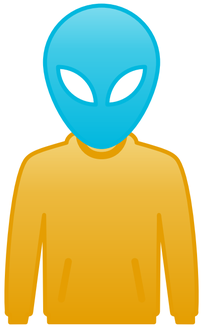
BACKDOOR THE MODEL



- **Inject small amount of malicious data into the benign traffic, which will not be detected as anomalous**
  - The model will not detect the backdoored traffic as malicious
  - Security gateway uses this data to train the local model
  - Local model will be sent to the aggregator, hence affecting the global model
- **Challenges of the implanted backdoor**
  - To evade
    - the traffic anomaly detection of the global model and
    - the model anomaly detection of the aggregator

4 TAXONOMIES OF ATTACKS: FOCUS ON BACKDOOR ATTACKS [2-3]



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Untargeted attacks

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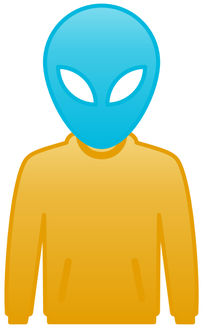

Objective

Untargeted attacks

Targeted/backdoor attacks

Input-instance-key strategies

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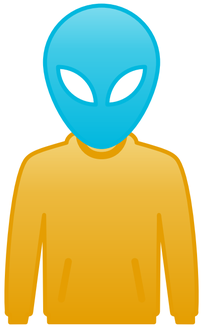

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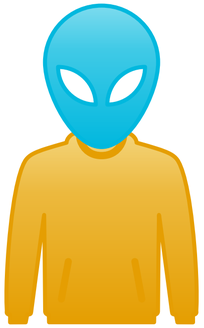

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Blended injection strategy

Accessory injection strategy

Blended accessory injection strategy

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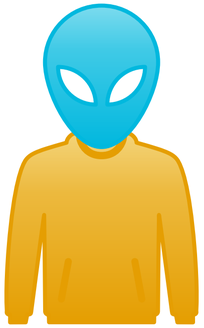

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Number of patterns

Single pattern attack

Multi-backdoor attack (Sybil)

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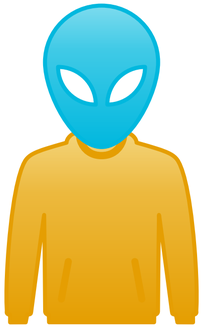

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Design of the pattern

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- Accessory injection strategy
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Number of patterns

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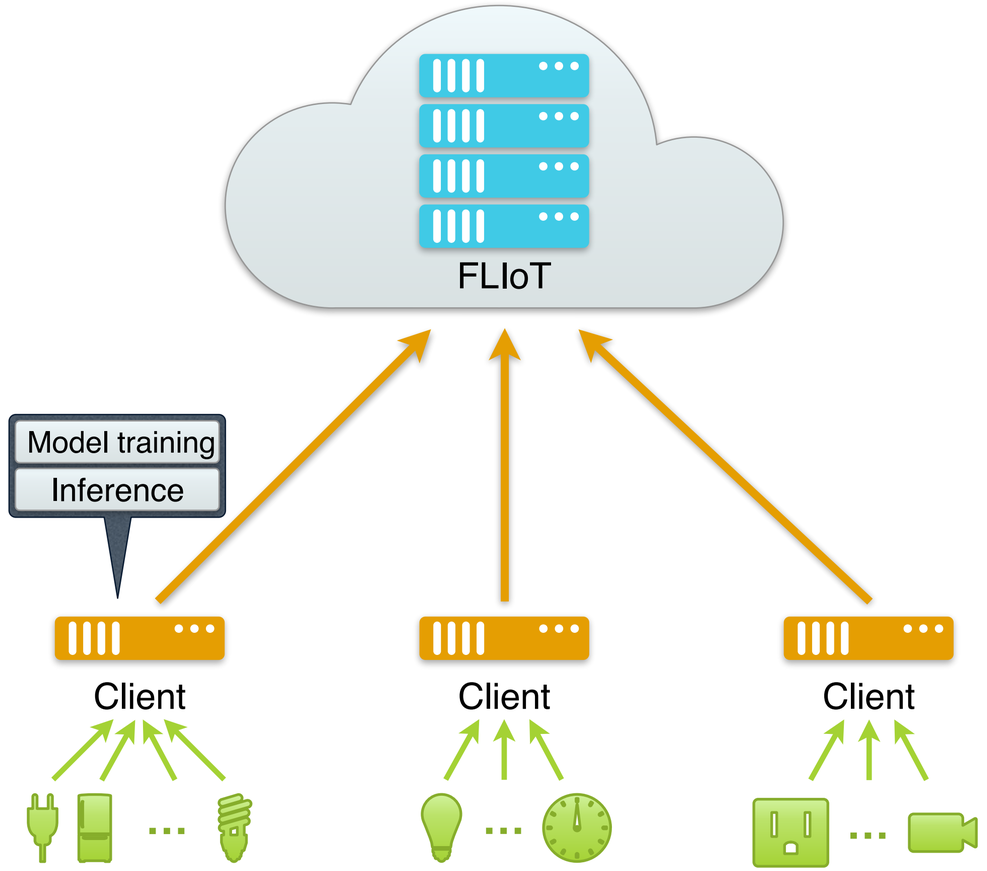
- Multi-backdoor attack (Sybil)

Variability over time

- Static attack
- Dynamic attack

THREAT MODEL FOR POISONING ATTACKS [4]

- **Data poisoning attacks**
  - Implant a backdoor in the aggregated model to incorrectly classify malicious data as benign.
- **Attacker's goal**
  - To corrupt the global model by aggregator so that the model wouldn't detect malicious traffic as anomalous.
- **The attacker controls a number of IoT devices and can also connect their devices to the security gateway**



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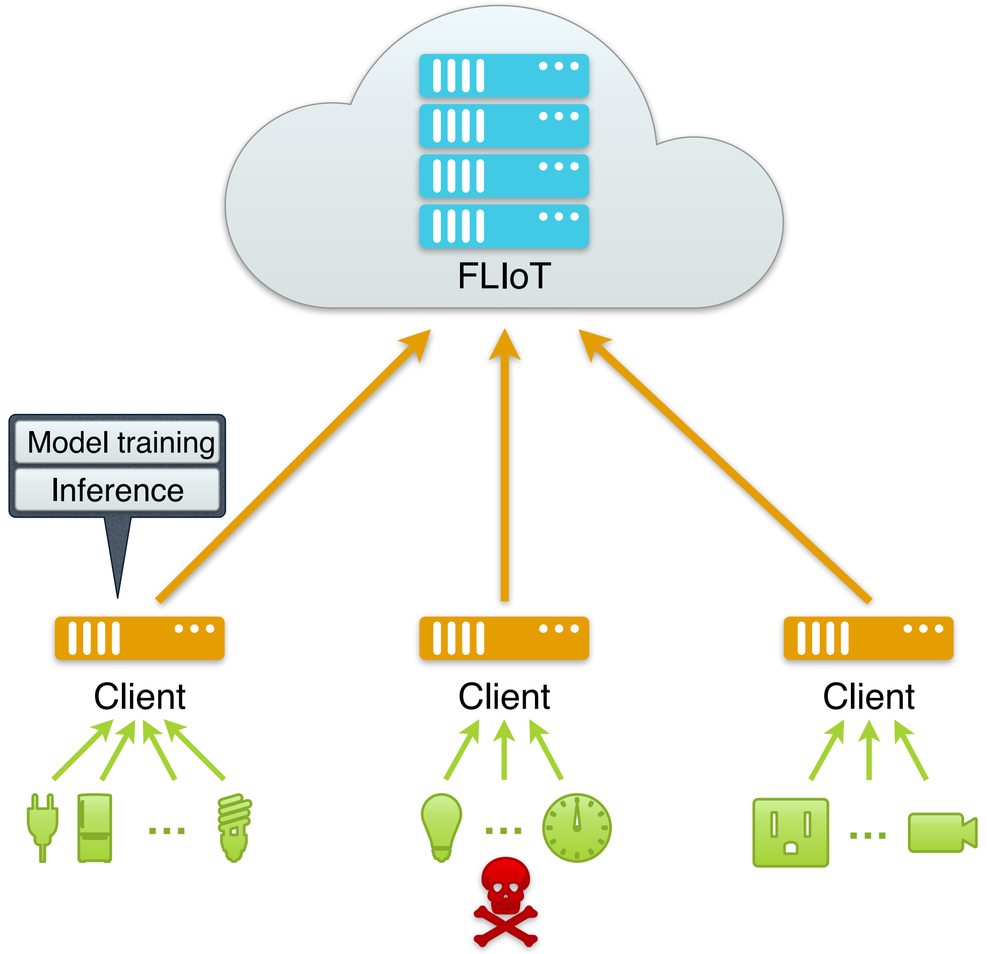
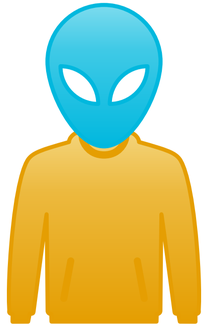


4 TAXONOMIES OF ATTACKS: FOCUS ON POISONED PART OF FL SCHEME



Poisoned part

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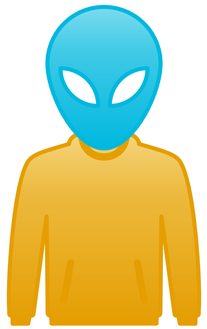
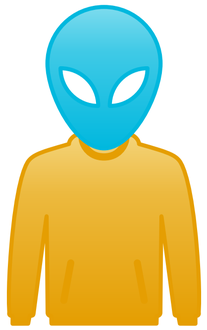


Poisoned part

Data-poisoning attacks

- Label-flipping attack
- Poisoning samples attack
- Out-of-distribution attack

4 TAXONOMIES OF ATTACKS: FOCUS ON POISONED PART OF FL SCHEME



Poisoned part

Data-poisoning attacks	Model-poisoning attacks
Label-flipping attack	Random weights generation
Poisoning samples attack	Optimization methods
Out-of-distribution attack	Information leakage

ASSOCIATED RESEARCH QUESTIONS

Léo Lavaur, Yann Busnel, Fabien Autrel. *Systematic Analysis of Label-flipping Attacks against Federated Learning in Collaborative Intrusion Detection Systems*. 19th International Conference on Availability, Reliability and Security, Jul 2024, Vienna, Austria

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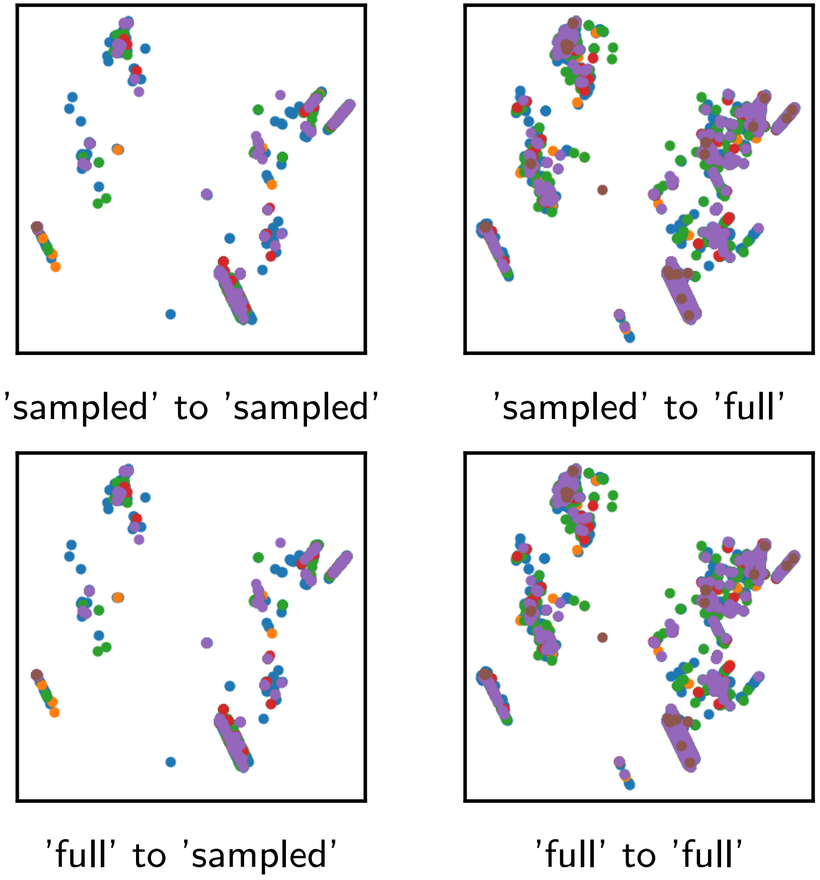
- **RQ4. Are IDS backdoors realistic using label-flipping attacks?**
- **RQ5. Is there a critical threshold where label-flipping attacks begin to impact performance?**

Léo Lavaur, Yann Busnel, Fabien Autrel. *Systematic Analysis of Label-flipping Attacks against Federated Learning in Collaborative Intrusion Detection Systems*. 19th International Conference on Availability, Reliability and Security, Jul 2024, Vienna, Austria

EXPERIMENTAL SETUP

Cross-projection of the malicious traffic from two datasets in two dimensions using PCA



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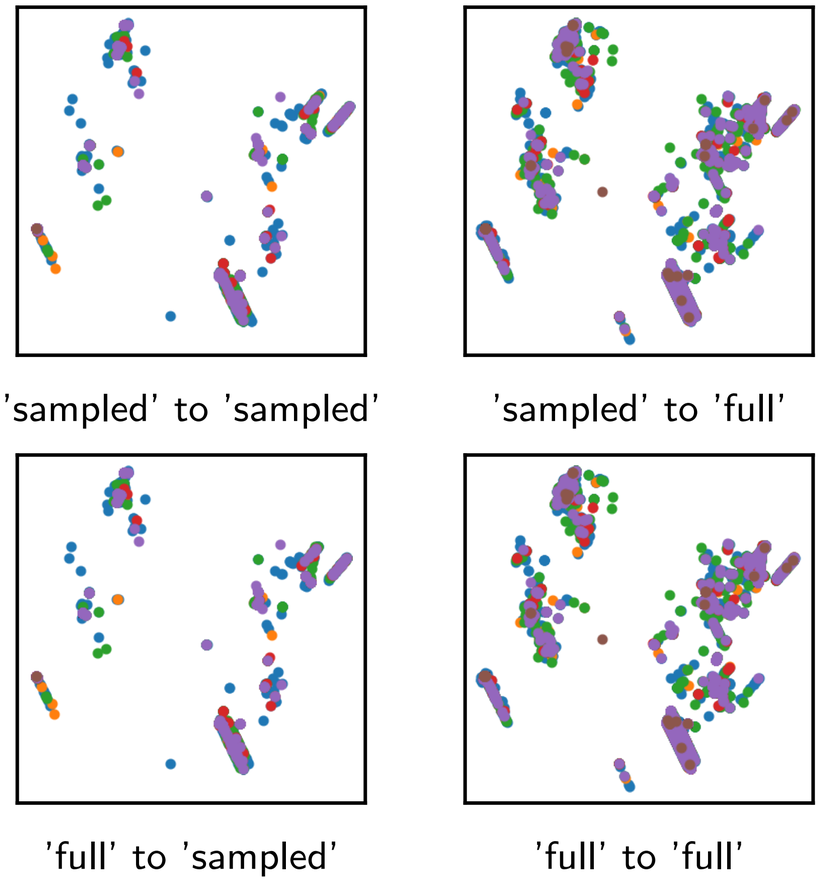

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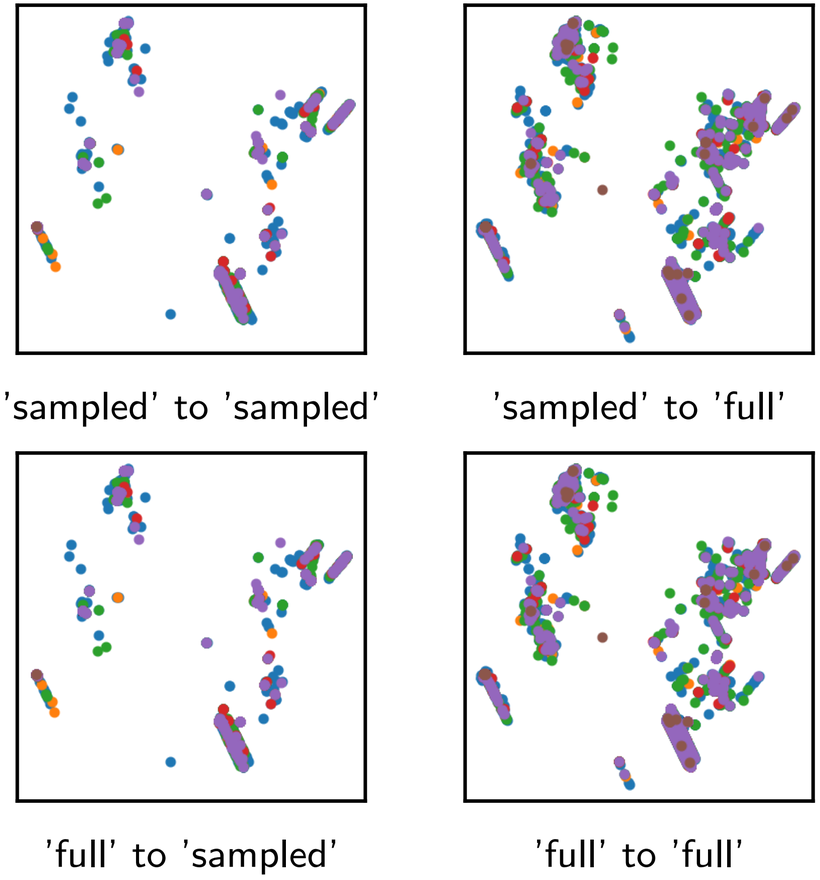

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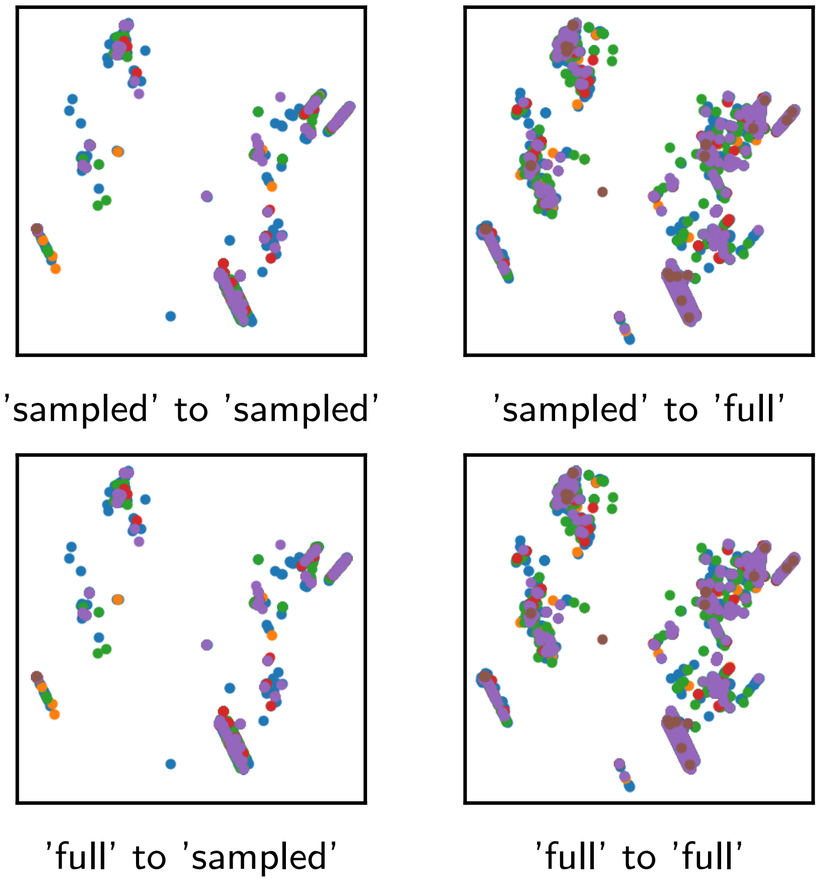

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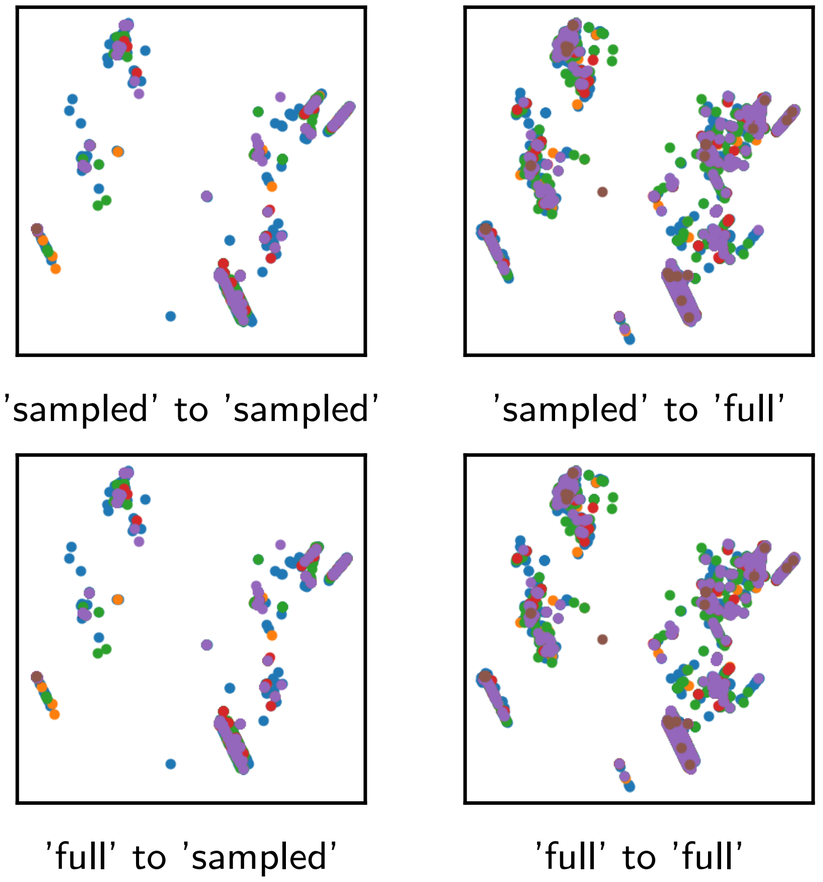

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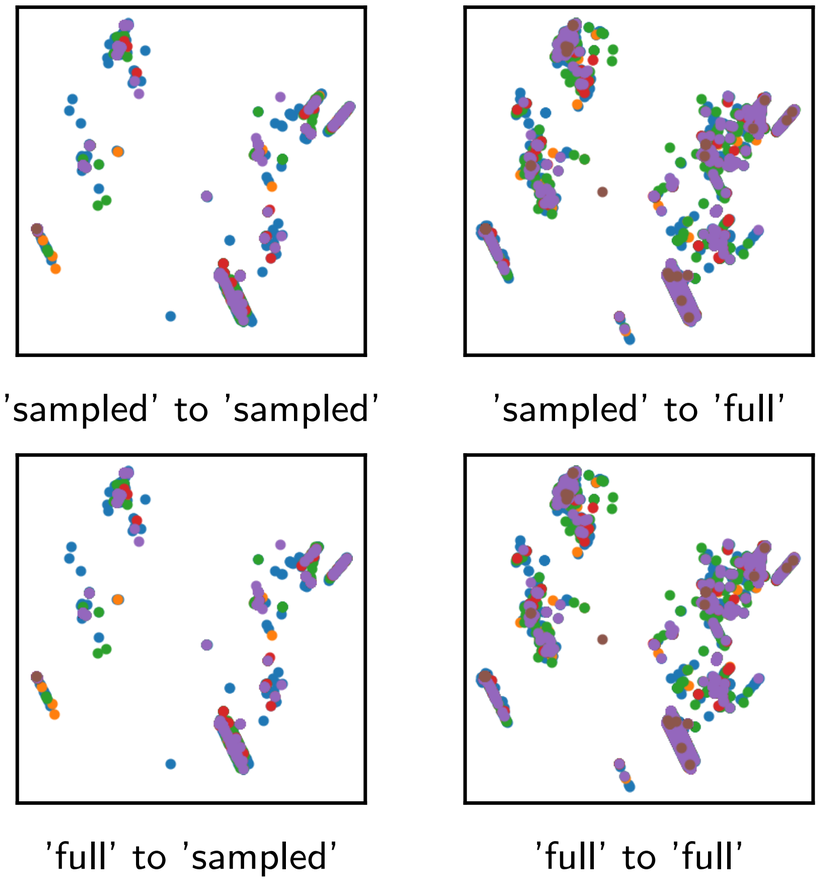

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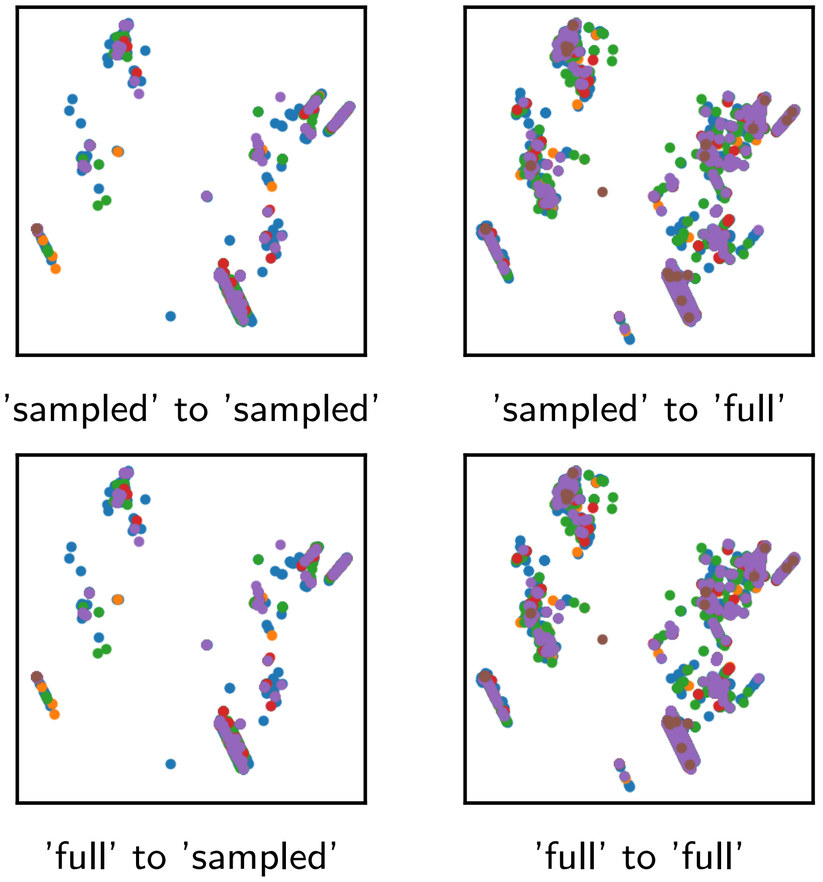

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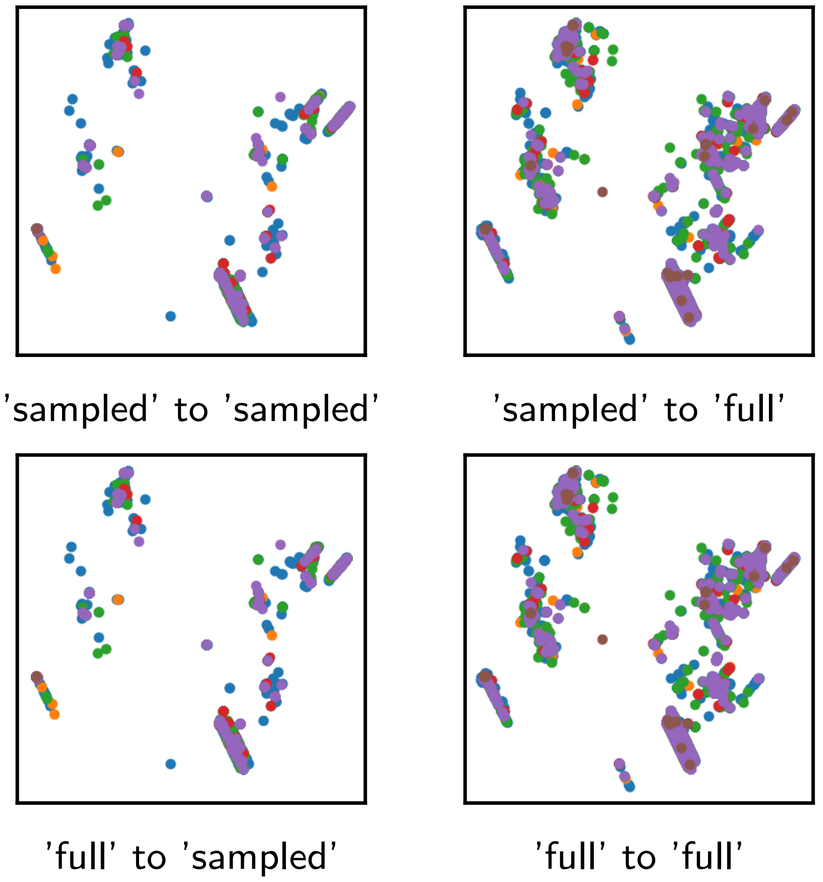

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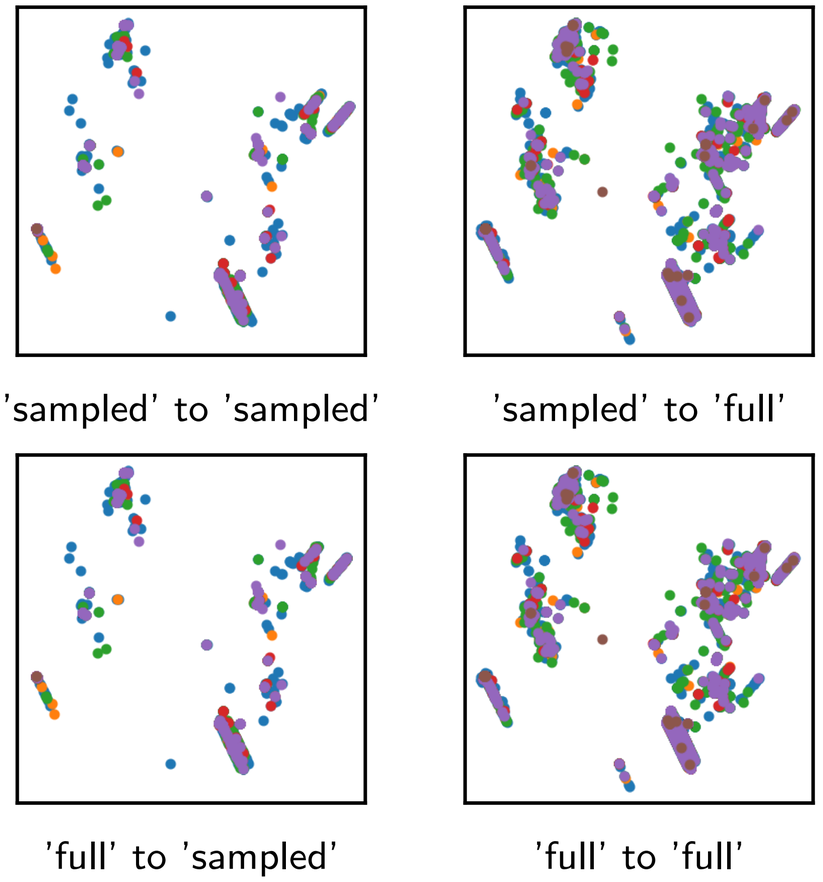

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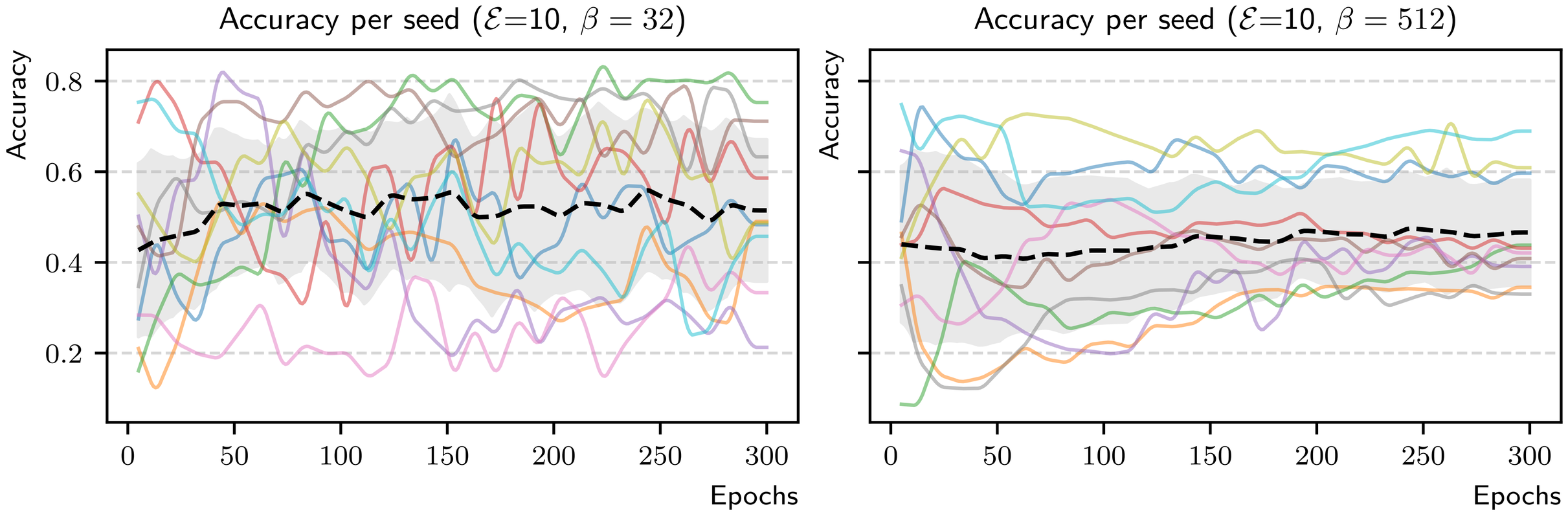
RQ1: IS THE BEHAVIOR OF POISONING ATTACKS PREDICTABLE?



Accuracy of the poisoned model by seed

Léo Lavaur, Yann Busnel, Fabien Autrel. *Systematic Analysis of Label-flipping Attacks against Federated Learning in Collaborative Intrusion Detection Systems*. 19th International Conference on Availability, Reliability and Security, Jul 2024, Vienna, Austria

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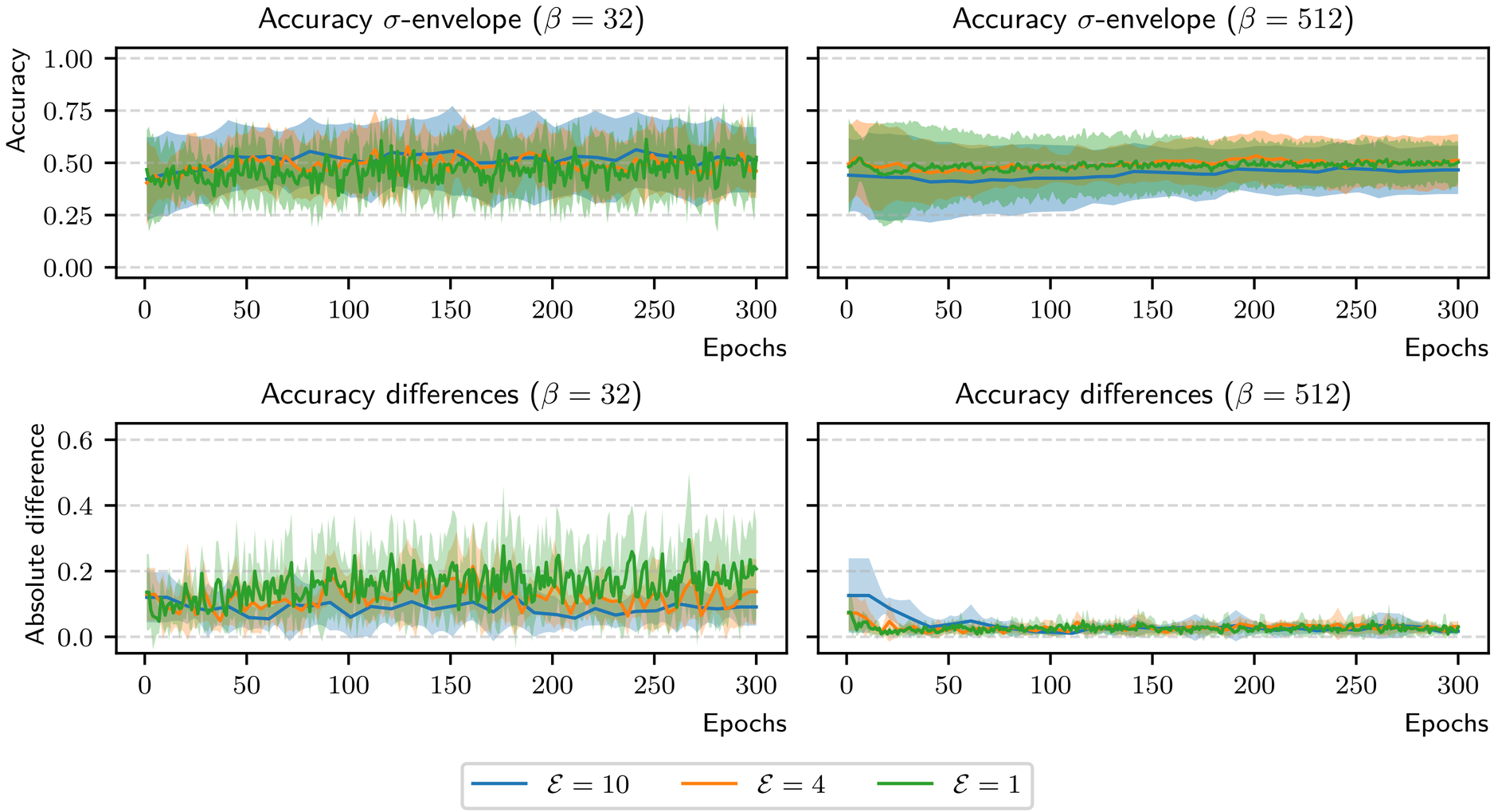

Predictability depending on the hyperparameters

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IMT-Université de Lille

UMR IRISA

RQ1: IS THE BEHAVIOR OF POISONING ATTACKS PREDICTABLE?

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Answer:

RQ1: IS THE BEHAVIOR OF POISONING ATTACKS PREDICTABLE?

Answer: Nope!

For more details on the other QRs, please consult the companion paper:

Léo Lavaur, Yann Busnel, Fabien Autrel. *Systematic Analysis of Label-flipping Attacks against Federated Learning in Collaborative Intrusion Detection Systems*. 19th International Conference on Availability, Reliability and Security, Jul 2024, Vienna, Austria

METHODS FOR FILTERING CONTRIBUTIONS IN FEDERATED LEARNING

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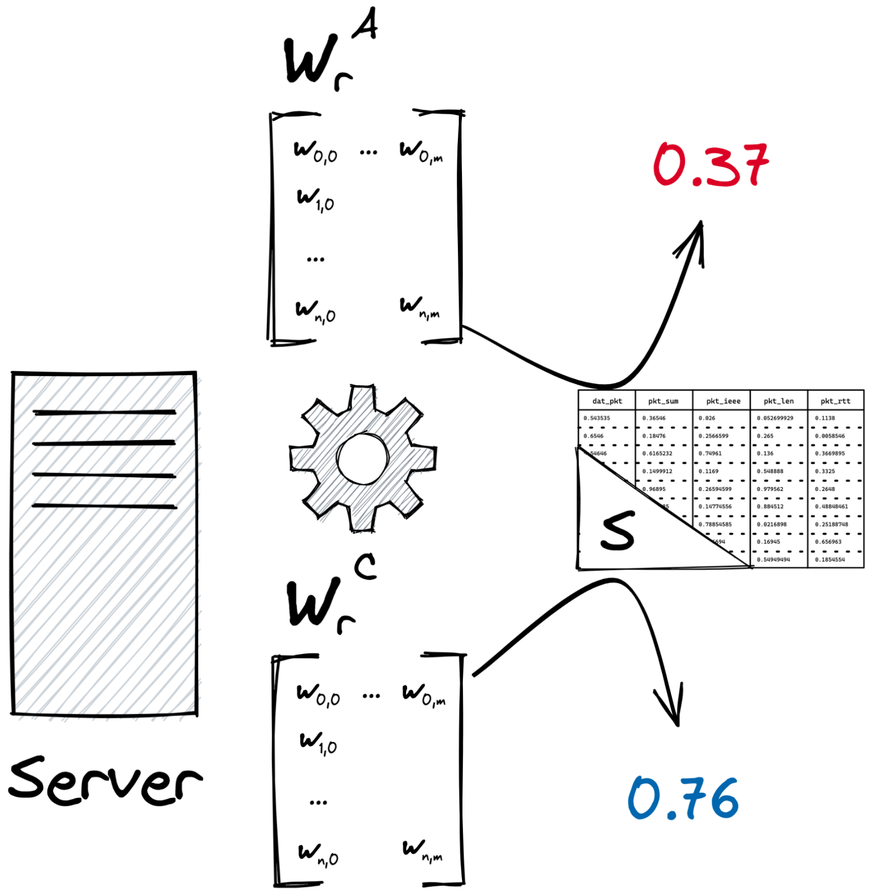
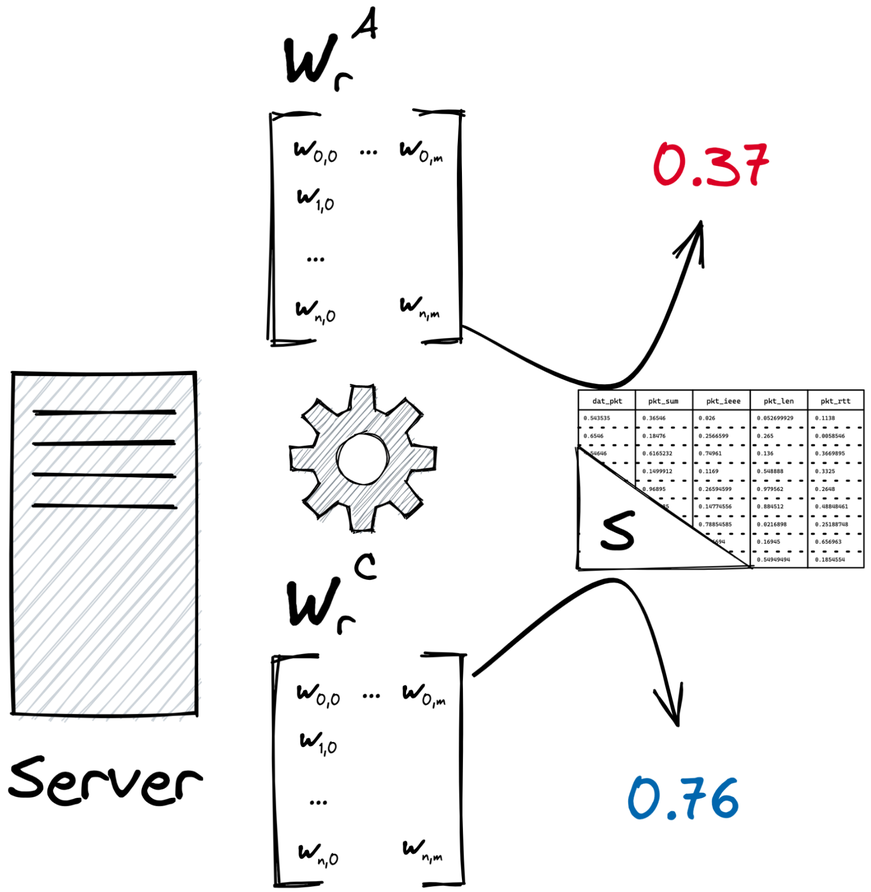
SERVER-SIDE EVALUATION [5]

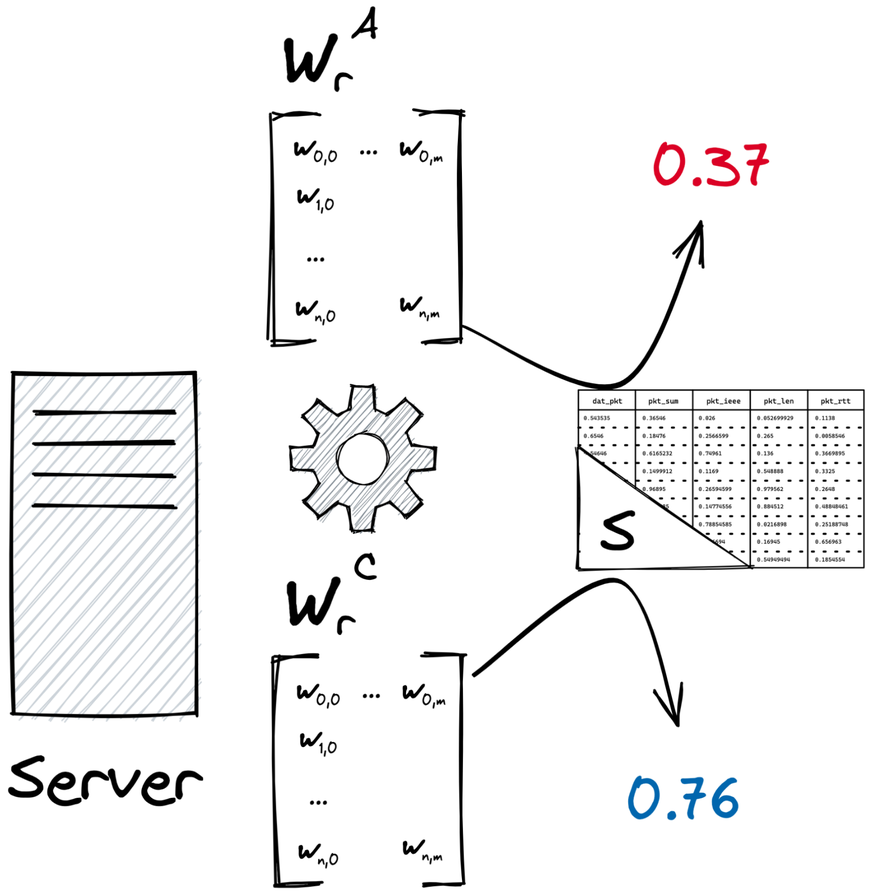


SERVER-SIDE EVALUATION [5]



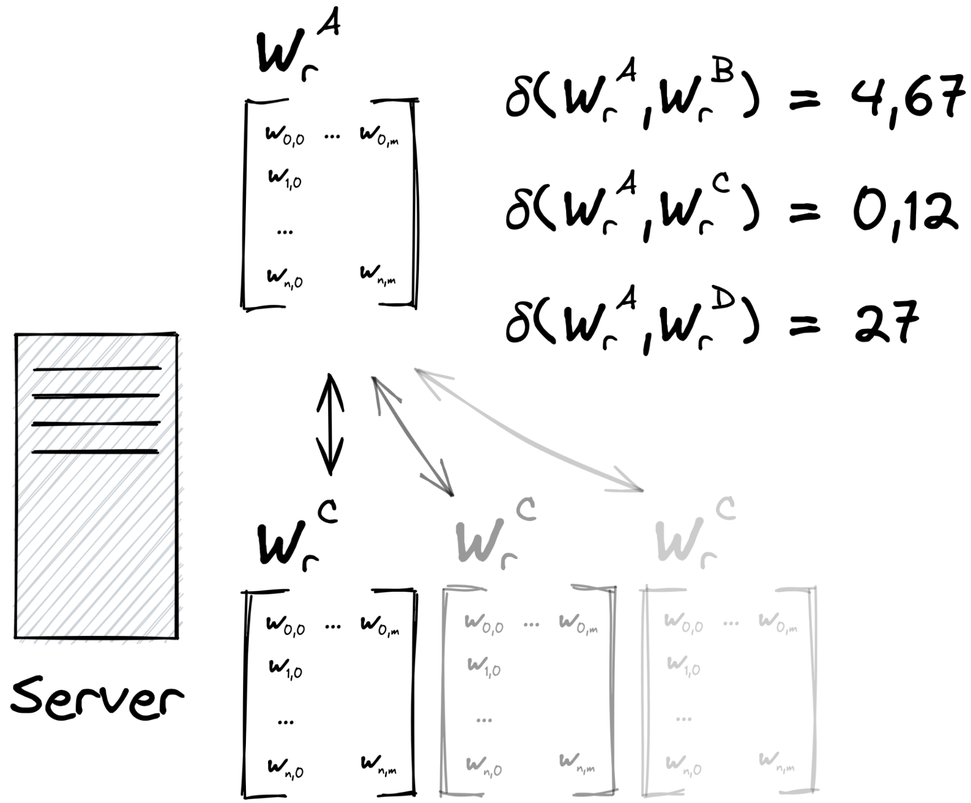
- **Compute test evaluation on updated models**
  - Exclude outlier clients

SERVER-SIDE EVALUATION [5]

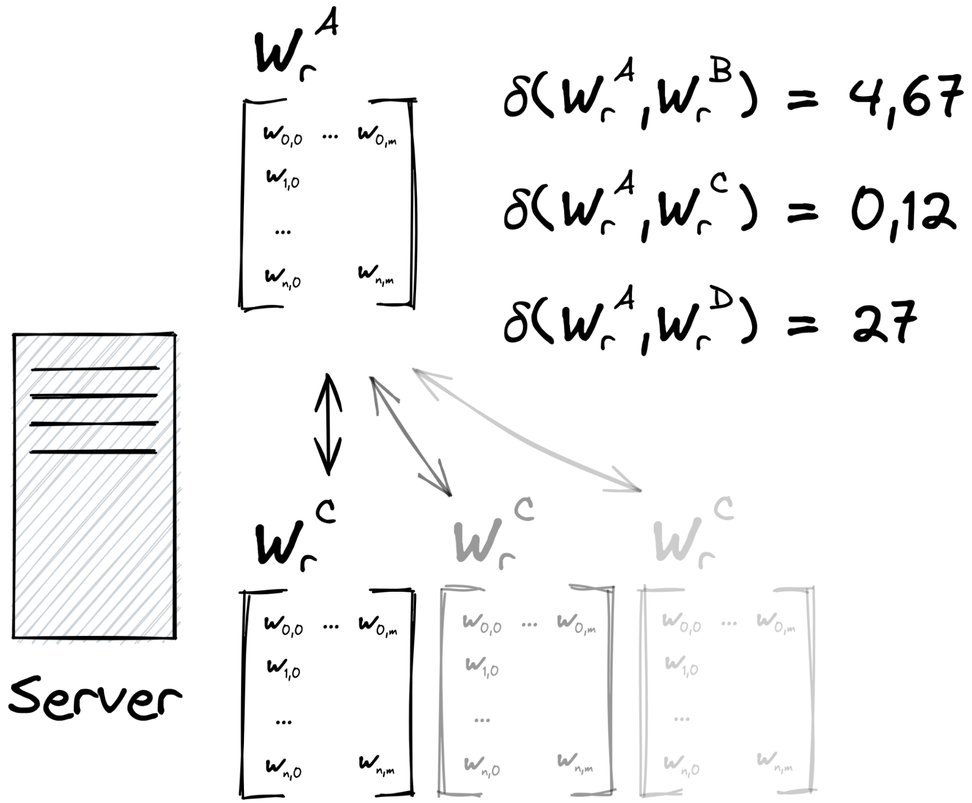


- **Compute test evaluation on updated models**
  - Exclude outlier clients
- **Limitation**
  - Only applicable in IID settings
  - Single source of truth
    - Representative test dataset
    - Server trustworthiness

SERVER-SIDE MODEL COMPARISON

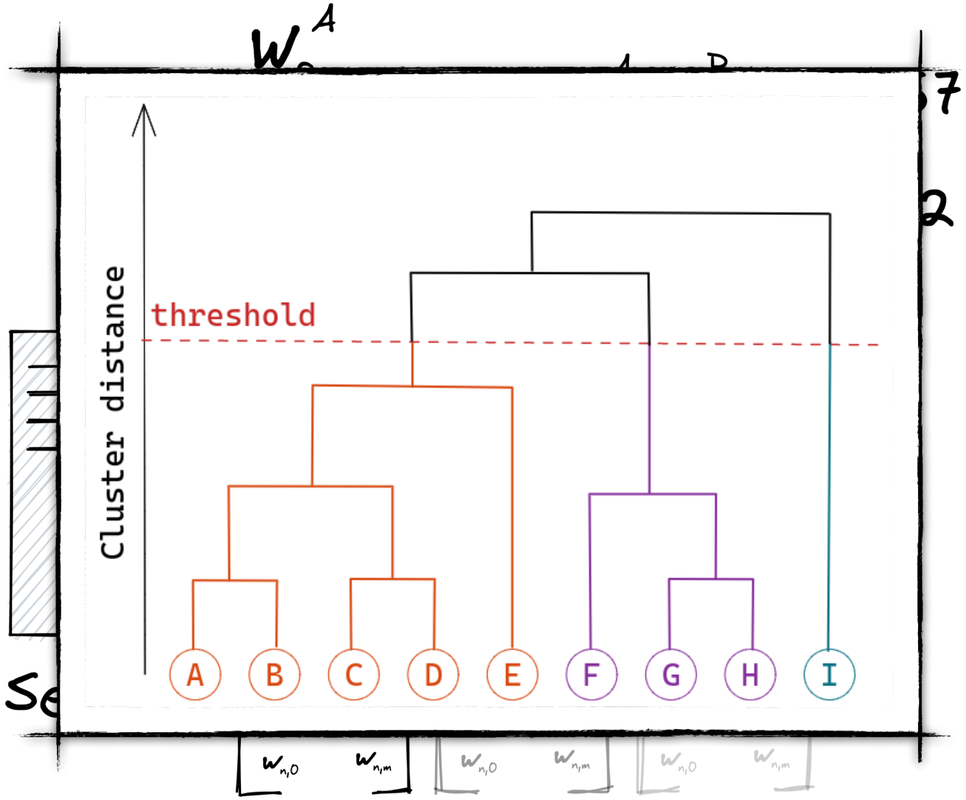


SERVER-SIDE MODEL COMPARISON



- **Clustering the clients by similarity based on their updates**
  - e.g. Hierarchical clustering [6]

SERVER-SIDE MODEL COMPARISON



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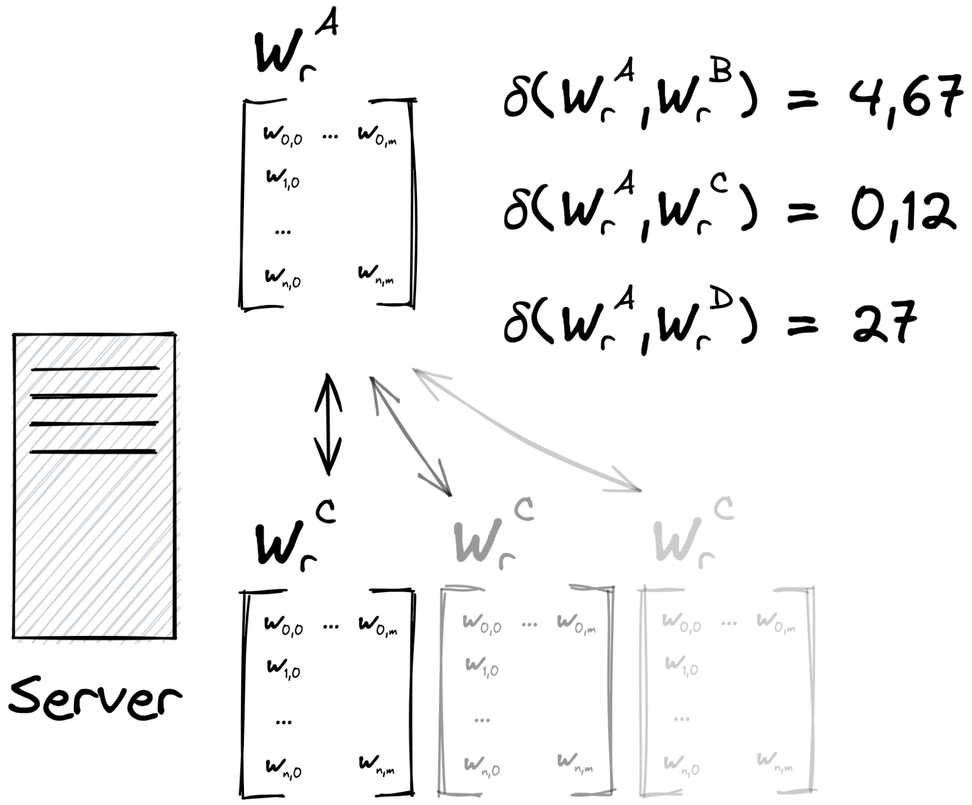
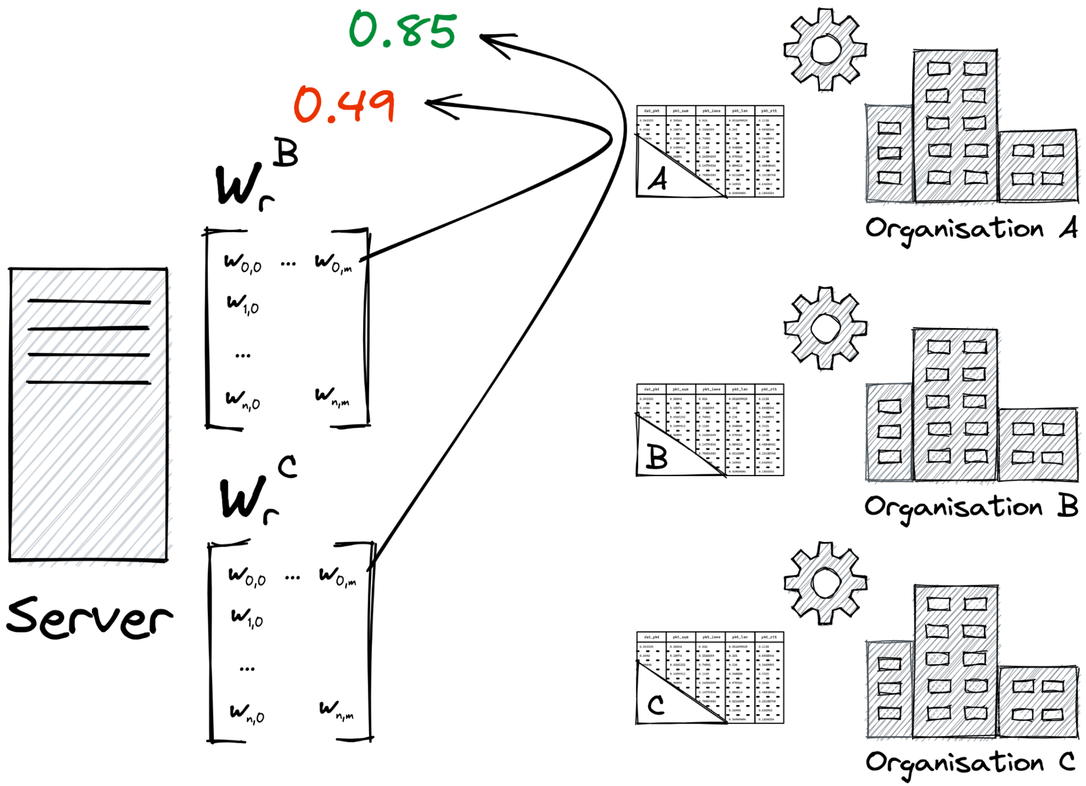
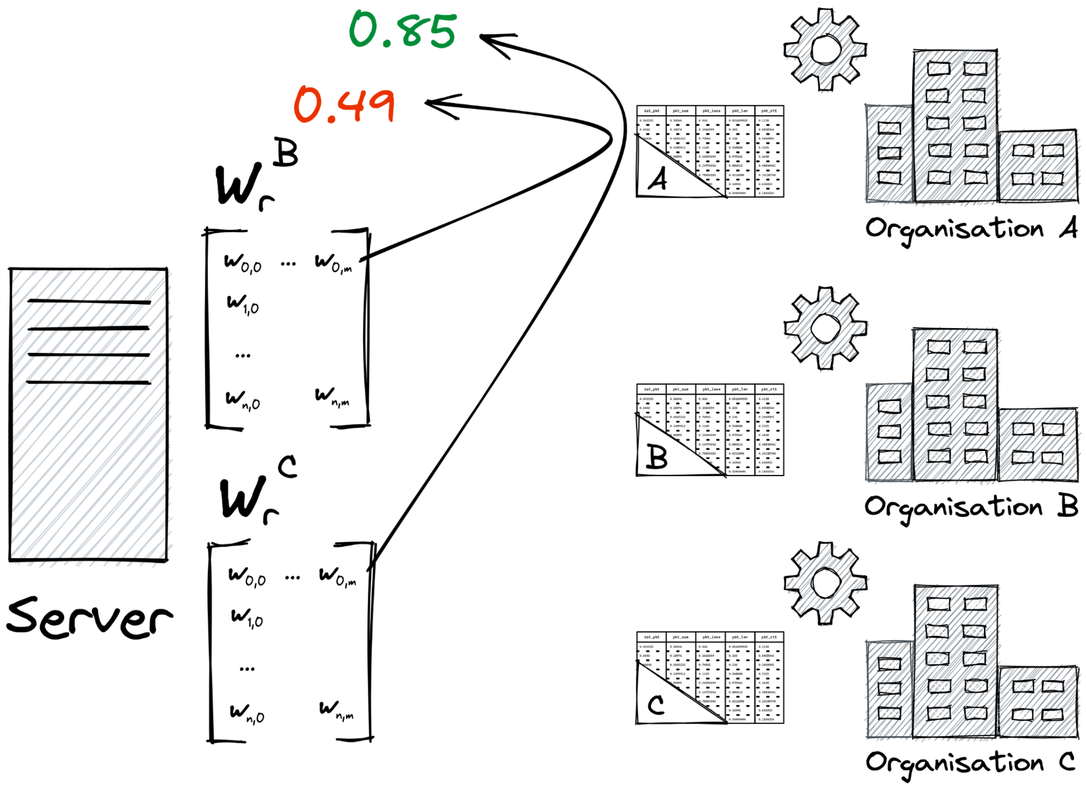


- **Clustering the clients by similarity based on their updates**
  - e.g. Hierarchical clustering [6]
- **Limitation**
  - Less related to client data
  - More appropriated for high-dimensional features

CLIENT-SIDE EVALUATION [7]



CLIENT-SIDE EVALUATION [7]



- **Cross-evaluation approach**
  - Merge update for « close » clients
  - Exclude outlier clients from the local point of view

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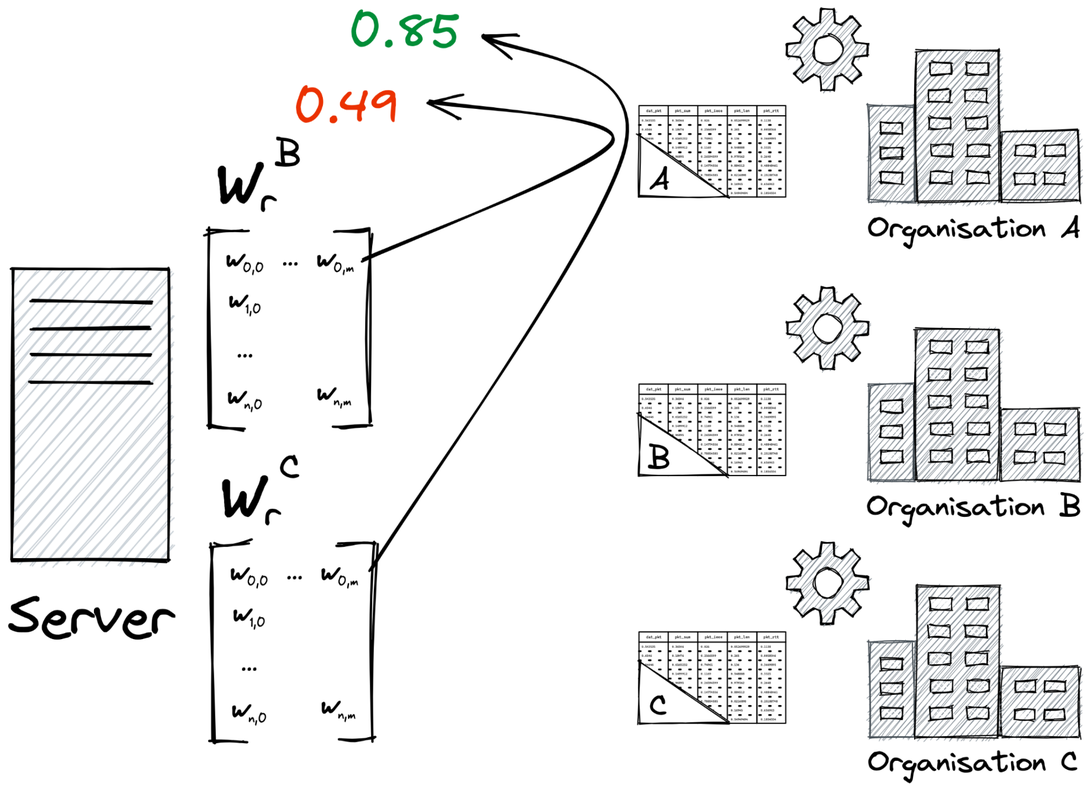


- **Cross-evaluation approach**
  - Merge update for « close » clients
  - Exclude outlier clients from the local point of view
- **Limitation**
  - High cost in cross-device settings

A CROSS-EVALUATION APPROACH FOR REPUTATION-AWARE MODEL WEIGHTING

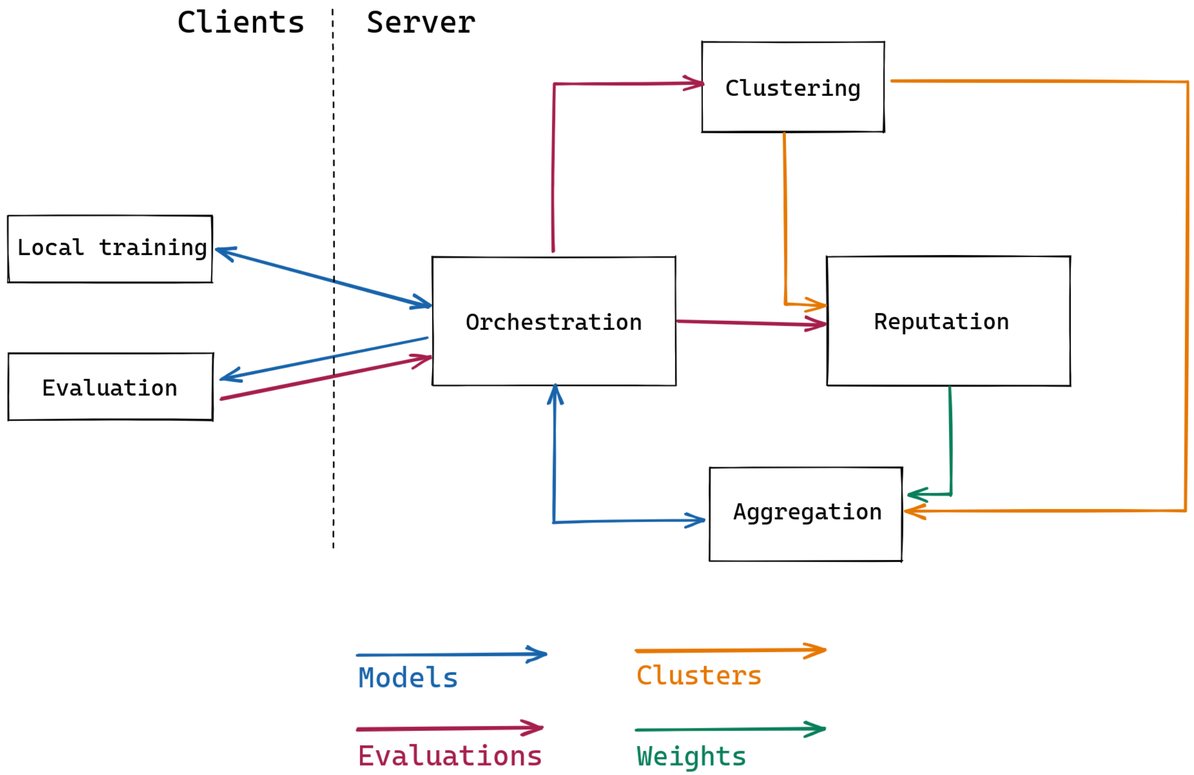
FILTERING CONTRIBUTIONS IN FEDERATED LEARNING FOR INTRUSION DETECTION

JOINT WORK BETWEEN YANN BUSNEL (IMT NORD EUROPE)
LEO LAVAUR, PIERRE-MARIE LECHEVALIER, ROMARIC LUDINARD,
MARC-OLIVER PAHL, GÉRALDINE TEXIER (IMT ATLANTIQUE)

IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

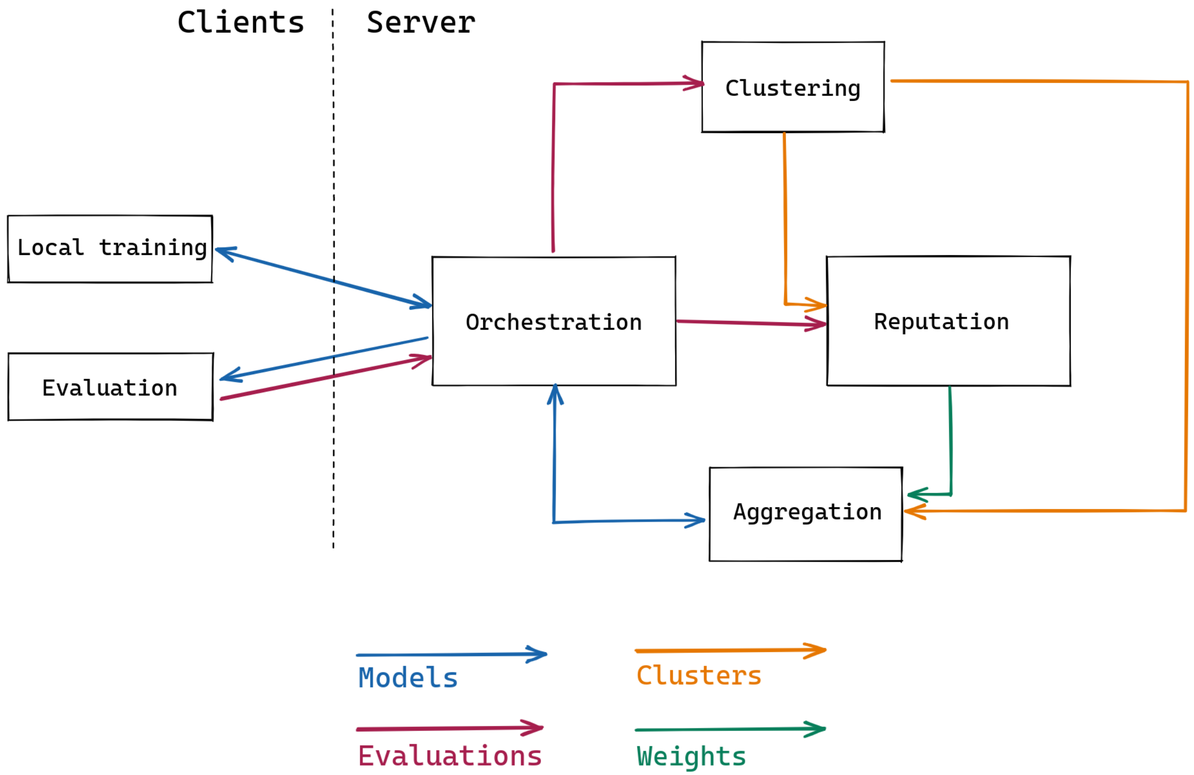
Proposed architecture



L. Lavaur, P.-M. Lechevalier, Y. Busnel, R. Ludinard, G. Texier, M.-O. Pahl. *RADAR: Model Quality Assessment for Reputation-aware Collaborative Federated Learning*. 43rd International Symposium on Reliable Distributed Systems (SRDS 2024), Charlotte, USA, Sept.2024

- **Objective:** Mitigate the impact of *bad* contributions to the local models

Proposed architecture



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- **Objective:** Mitigate the impact of *bad* contributions to the local models
  - How to evaluate models in highly heterogeneous settings?

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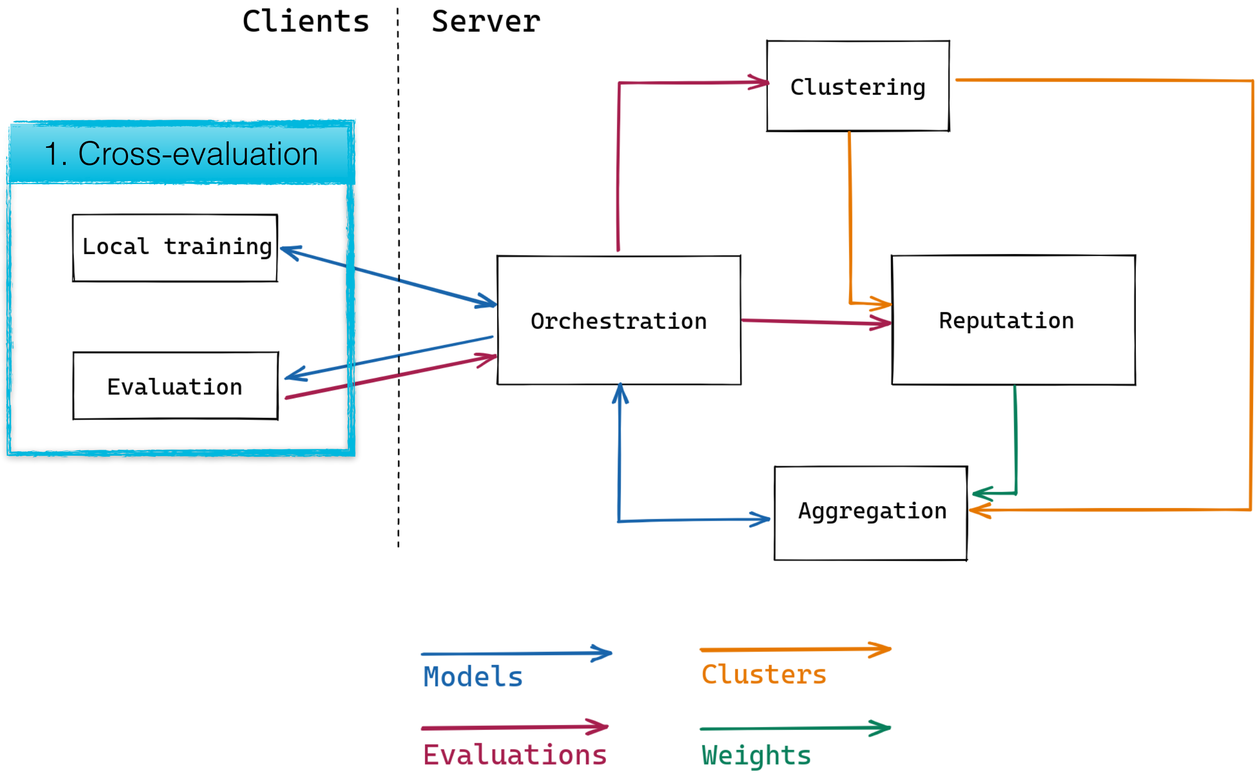

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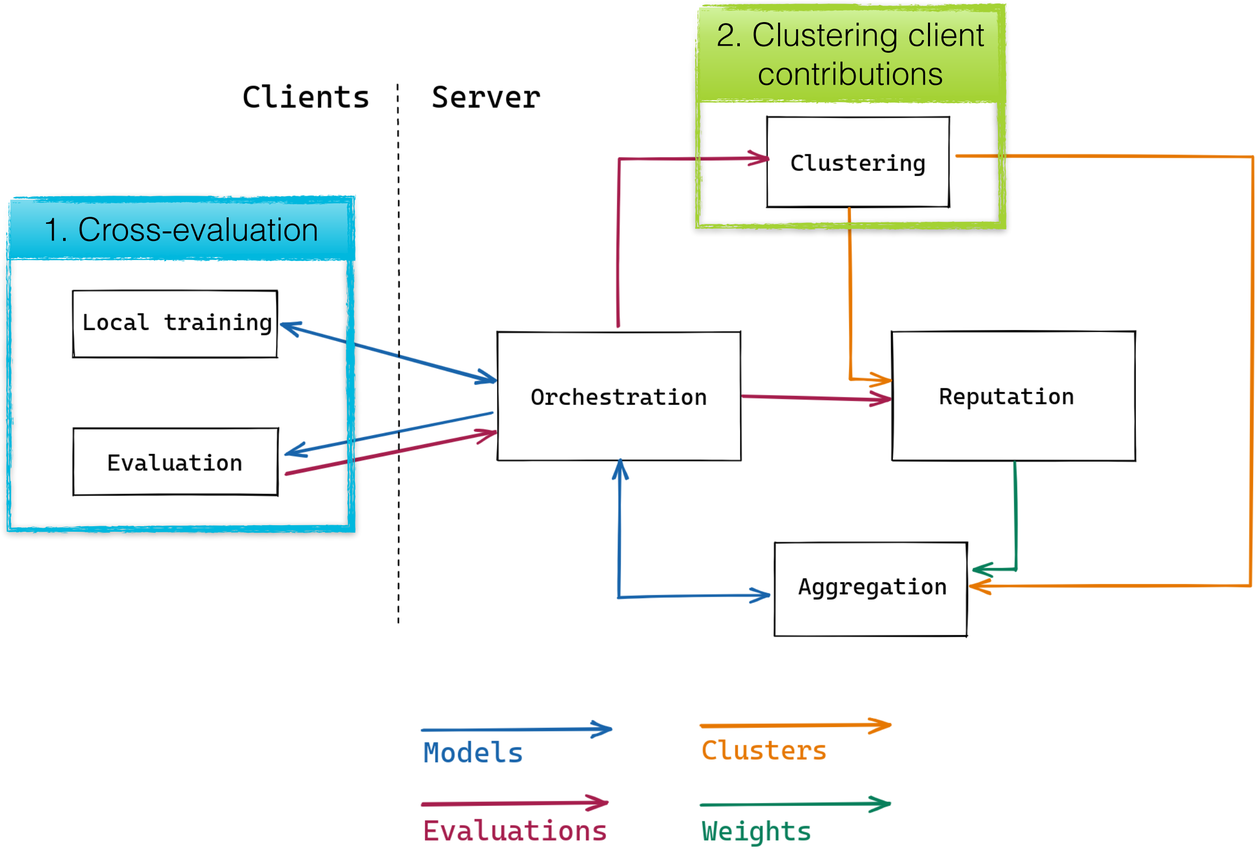

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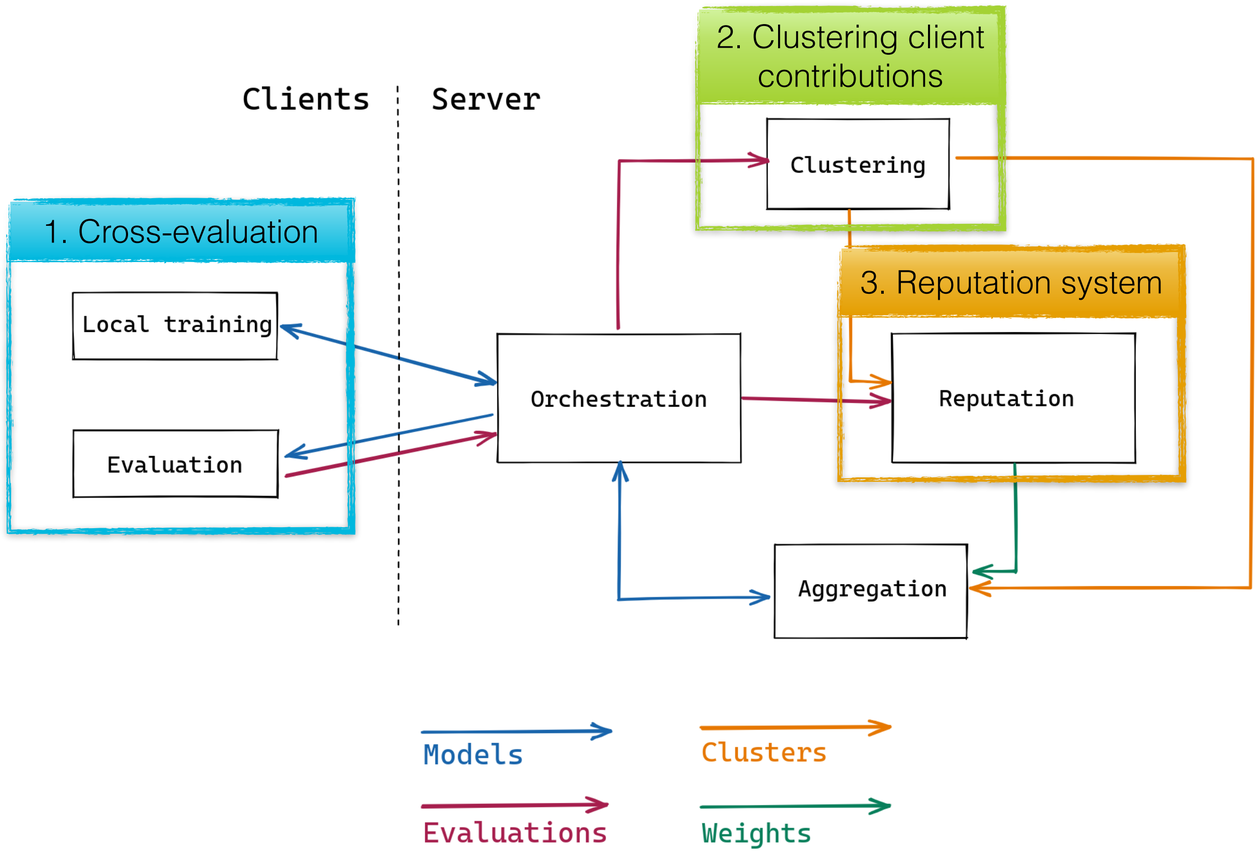
  - How to identify and discard similar but negative behaviors?

Proposed architecture



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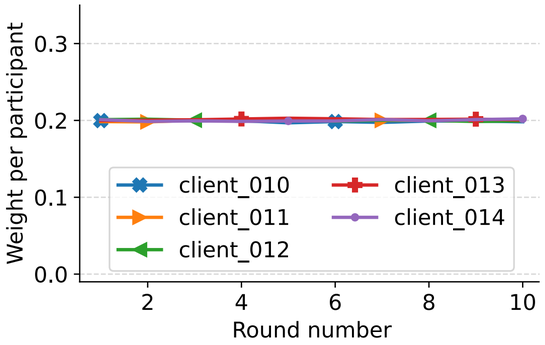
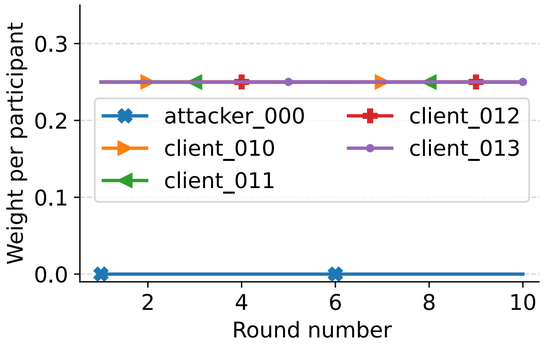
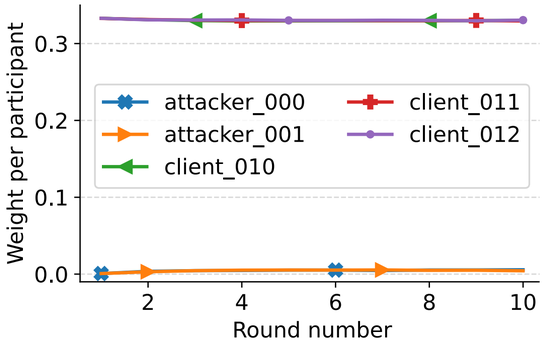
AGGREGATION WEIGHTS ρ FOR THE PARTICIPANTS COMING FROM THE BOT-IOT DATASET DEPENDING ON THE NUMBER OF BYZANTINES



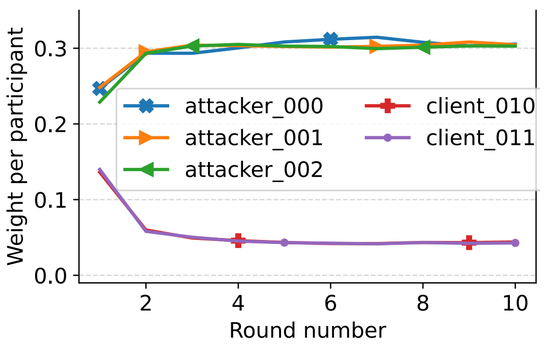
(a) `Benign`.



(b) `Lone 100T`.



(c) `Colluding minority 100T`.



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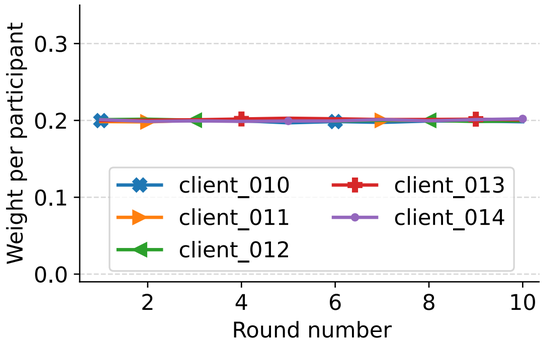
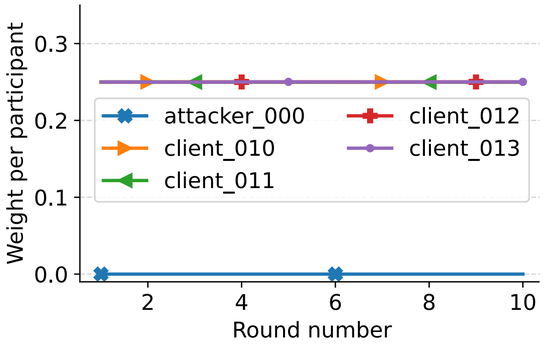
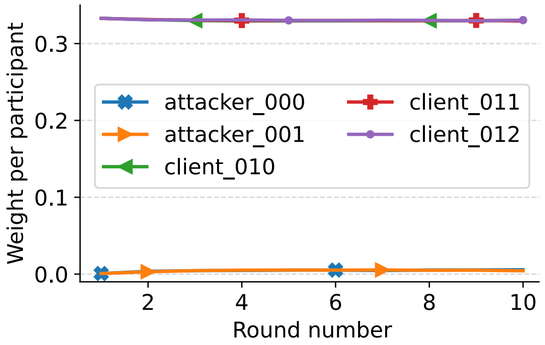


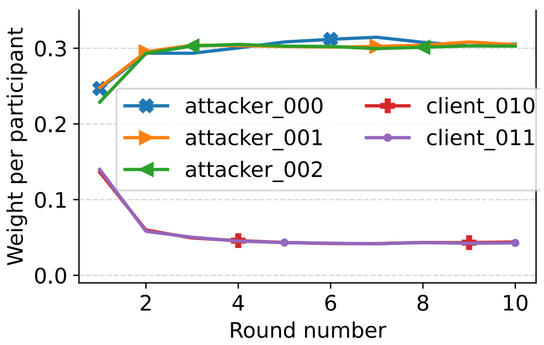
(a) `Benign`.



(b) `Lone 100T`.



(c) `Colluding minority 100T`.

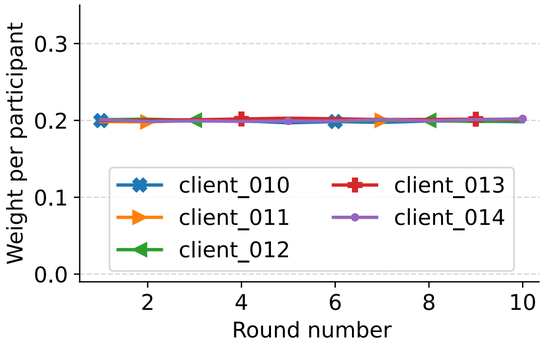


(d) `Colluding majority 100T`.

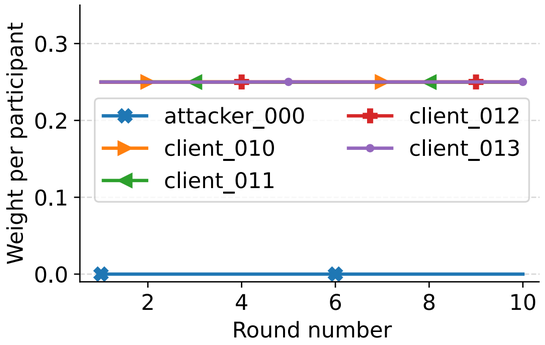
- **Byzantines are correctly penalized when they are a minority**

L. Lavaur, P.-M. Lechevalier, Y. Busnel, R. Ludinard, G. Texier, M.-O. Pahl. *RADAR: Model Quality Assessment for Reputation-aware Collaborative Federated Learning*. 43rd International Symposium on Reliable Distributed Systems (SRDS 2024), Charlotte, USA, Sept.2024

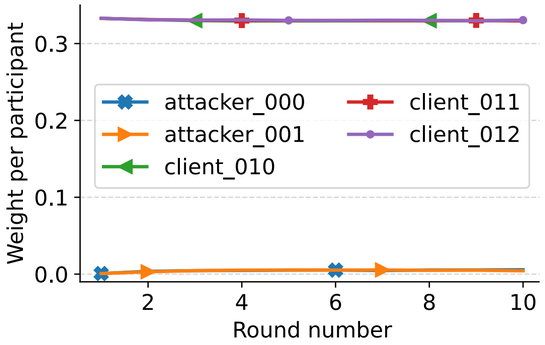
AGGREGATION WEIGHTS ρ FOR THE PARTICIPANTS COMING FROM THE BOT-IOT DATASET DEPENDING ON THE NUMBER OF BYZANTINES



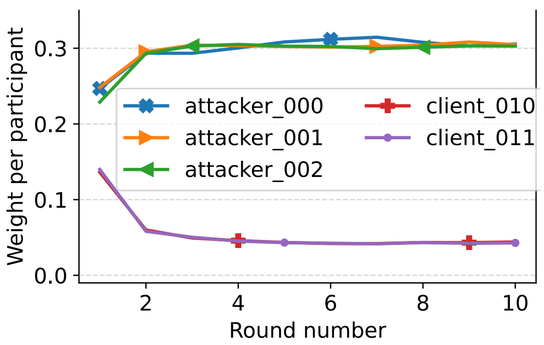
(a) `Benign`.



(b) `Lone 100T`.



(c) `Colluding minority 100T`.

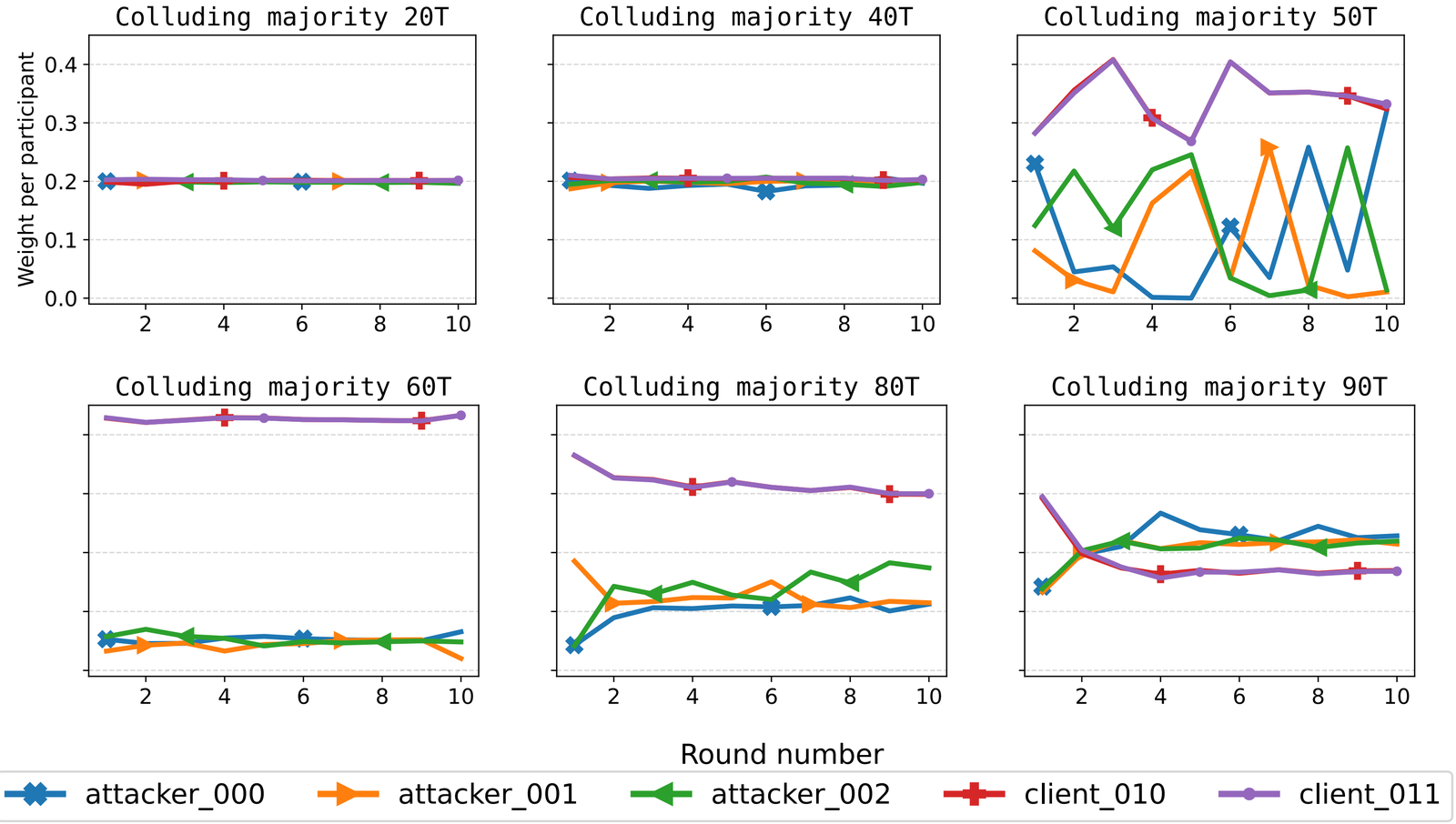


(d) `Colluding majority 100T`.

- **Byzantines are correctly penalized when they are a minority**
  - But gain precedence when they become the majority

L. Lavaur, P.-M. Lechevalier, Y. Busnel, R. Ludinard, G. Texier, M.-O. Pahl. *RADAR: Model Quality Assessment for Reputation-aware Collaborative Federated Learning*. 43rd International Symposium on Reliable Distributed Systems (SRDS 2024), Charlotte, USA, Sept.2024

AGGREGATION WEIGHTS ρ PER PARTICIPANT OF THE POISONED CLUSTER



L. Lavaur, P.-M. Lechevalier, Y. Busnel, R. Ludinard, G. Texier, M.-O. Pahl. *RADAR: Model Quality Assessment for Reputation-aware Collaborative Federated Learning*. 43rd International Symposium on Reliable Distributed Systems (SRDS 2024), Charlotte, USA, Sept.2024

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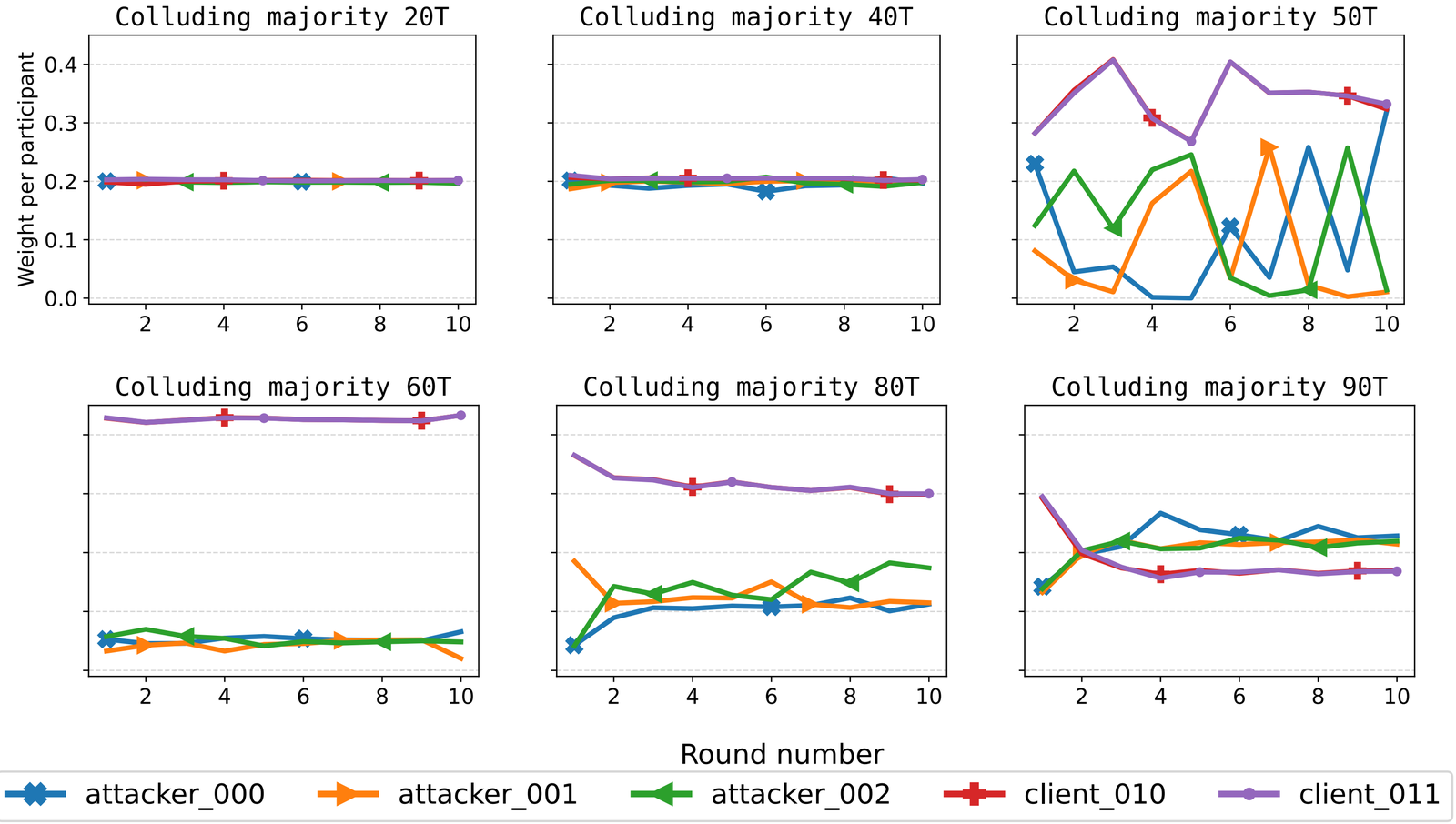

- **Even attackers are a majority, they gain only for higher poisoning rates (≥90%)**

L. Lavaur, P.-M. Lechevalier, Y. Busnel, R. Ludinard, G. Texier, M.-O. Pahl. *RADAR: Model Quality Assessment for Reputation-aware Collaborative Federated Learning*. 43rd International Symposium on Reliable Distributed Systems (SRDS 2024), Charlotte, USA, Sept.2024

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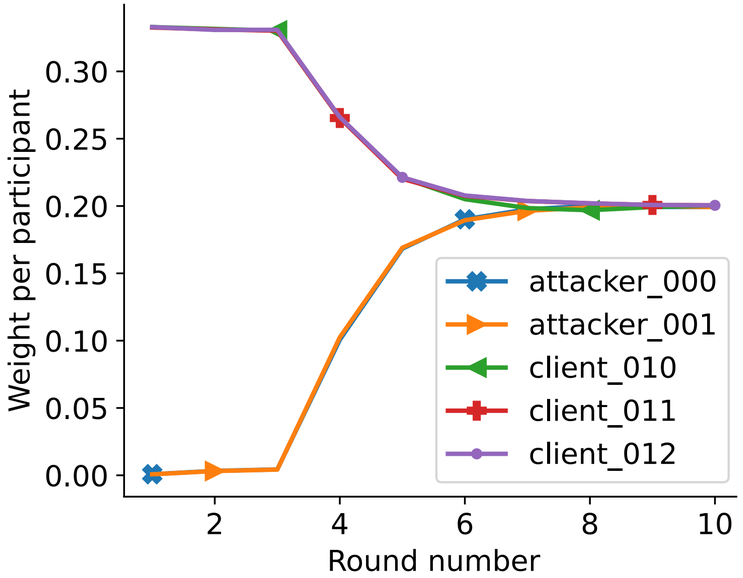
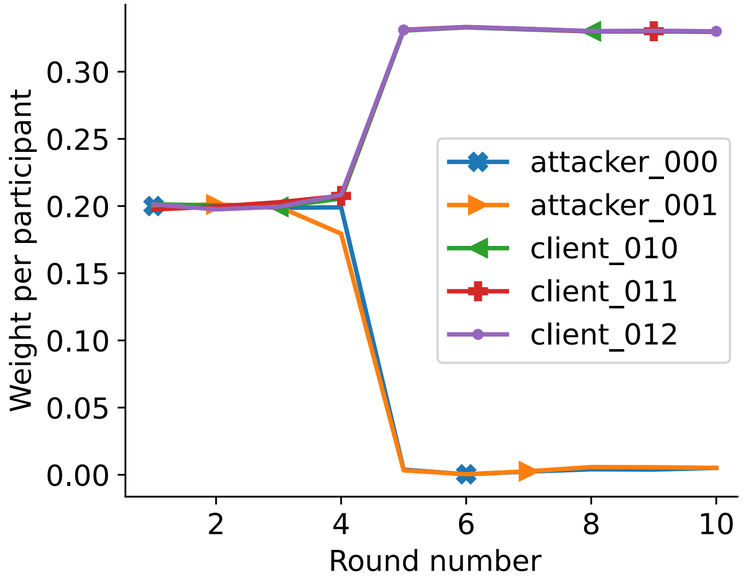


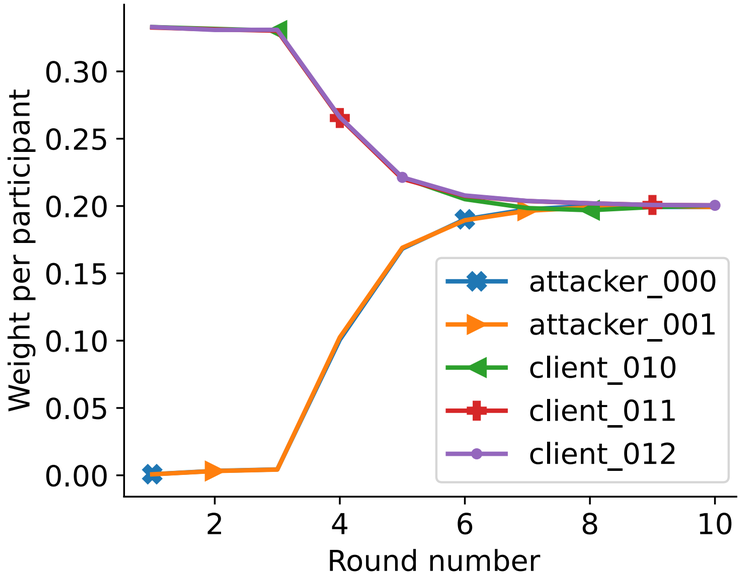
(a) Attackers act with 100% *noisiness*, but become benign on round 3.



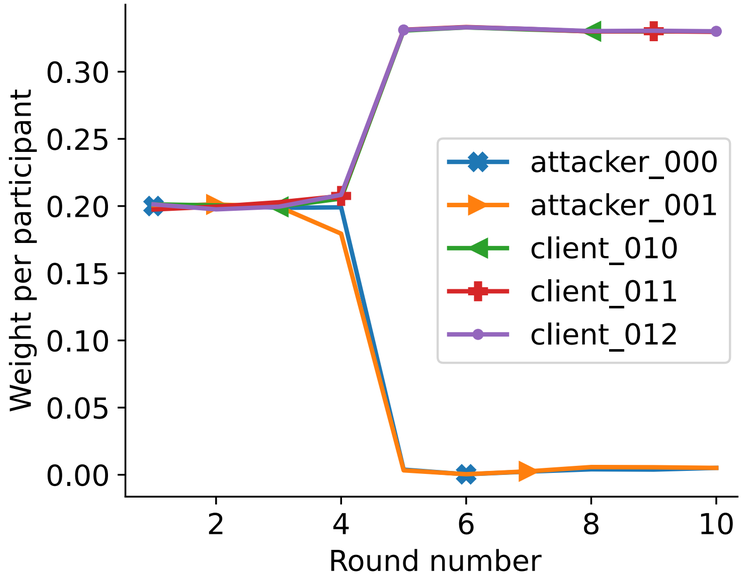
(b) Attackers start benign, and increase *noisiness* by 20% each round when $r \geq 3$.

L. Lavaur, P.-M. Lechevalier, Y. Busnel, R. Ludinard, G. Texier, M.-O. Pahl. *RADAR: Model Quality Assessment for Reputation-aware Collaborative Federated Learning*. 43rd International Symposium on Reliable Distributed Systems (SRDS 2024), Charlotte, USA, Sept.2024

AGGREGATION WEIGHTS ρ PER PARTICIPANT OF THE POISONED CLUSTER



(a) Attackers act with 100% *noisiness*, but become benign on round 3.



(b) Attackers start benign, and increase *noisiness* by 20% each round when $r \geq 3$.

- **Attackers are forgiven over time**
- **Reputation system reacts quickly to newly detected attackers.**

L. Lavaur, P.-M. Lechevalier, Y. Busnel, R. Ludinard, G. Texier, M.-O. Pahl. *RADAR: Model Quality Assessment for Reputation-aware Collaborative Federated Learning*. 43rd International Symposium on Reliable Distributed Systems (SRDS 2024), Charlotte, USA, Sept.2024

HANDS-ON! — PART 3

FEDERATED LEARNING FOR SECURITY

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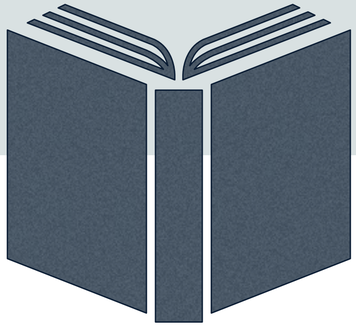

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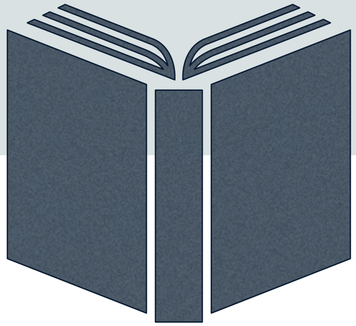

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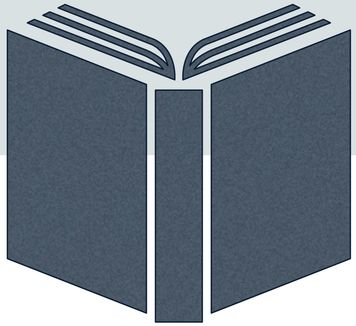

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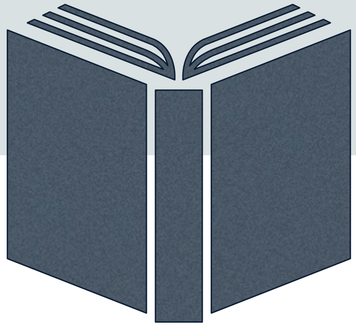

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