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

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

FEDERATED LEARNING × SECURITY IN NETWORK MANAGEMENT

YANN BUSNEL
IMT NORD EUROPE

LEO LAVAUR
IMT ATLANTIQUE

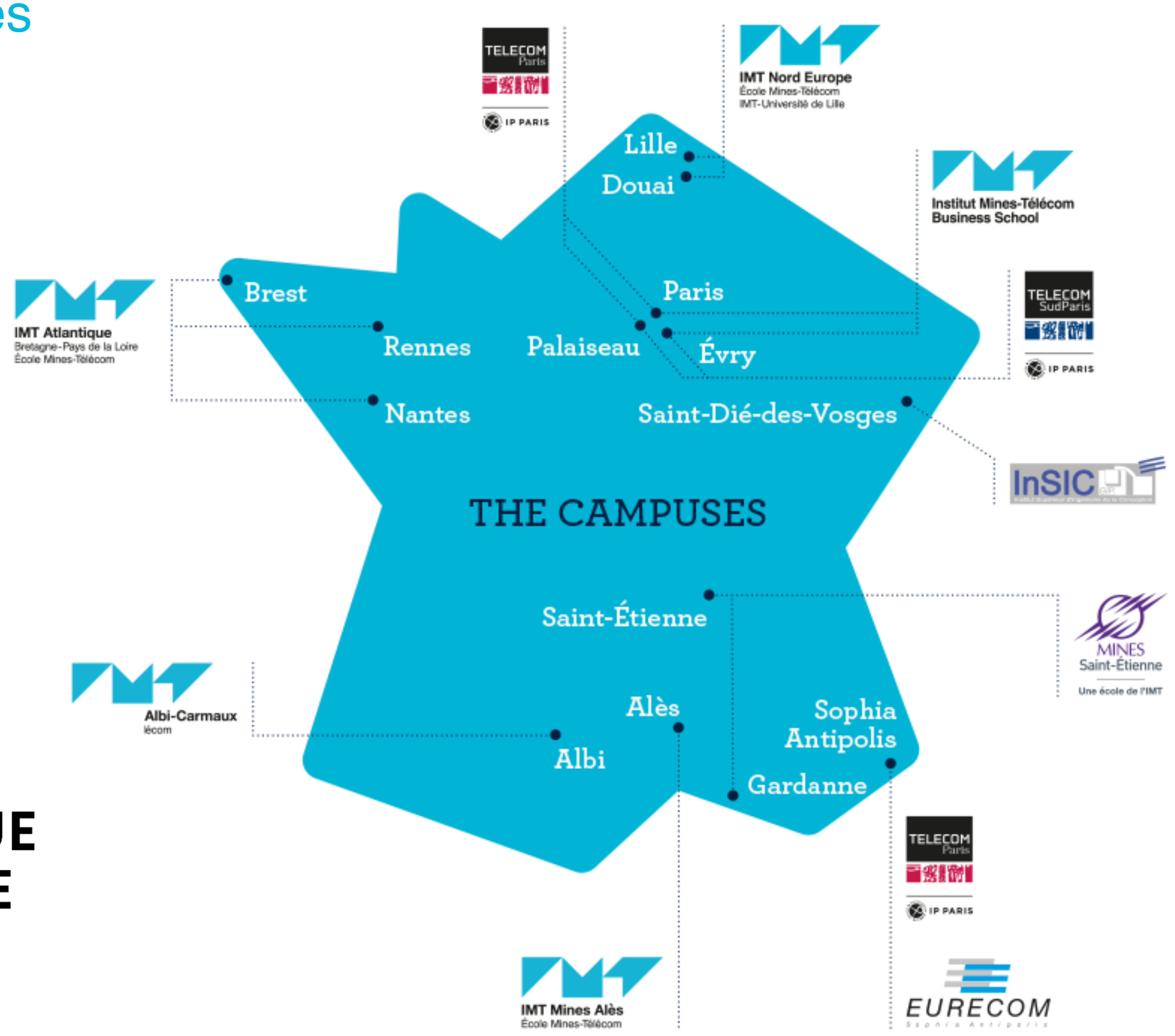
OCTOBER 04TH, 2023 — IEEE NOF — IZMIR, TURKEY

UMR IRISA

WHAT IS IMT?

8 Technological Universities
2 Subsidiaries

Institut Mines-Télécom



RÉPUBLIQUE
FRANÇAISE
Liberté
Égalité
Fraternité

under the aegis of the
Ministry of Industry and
Digital Communications

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

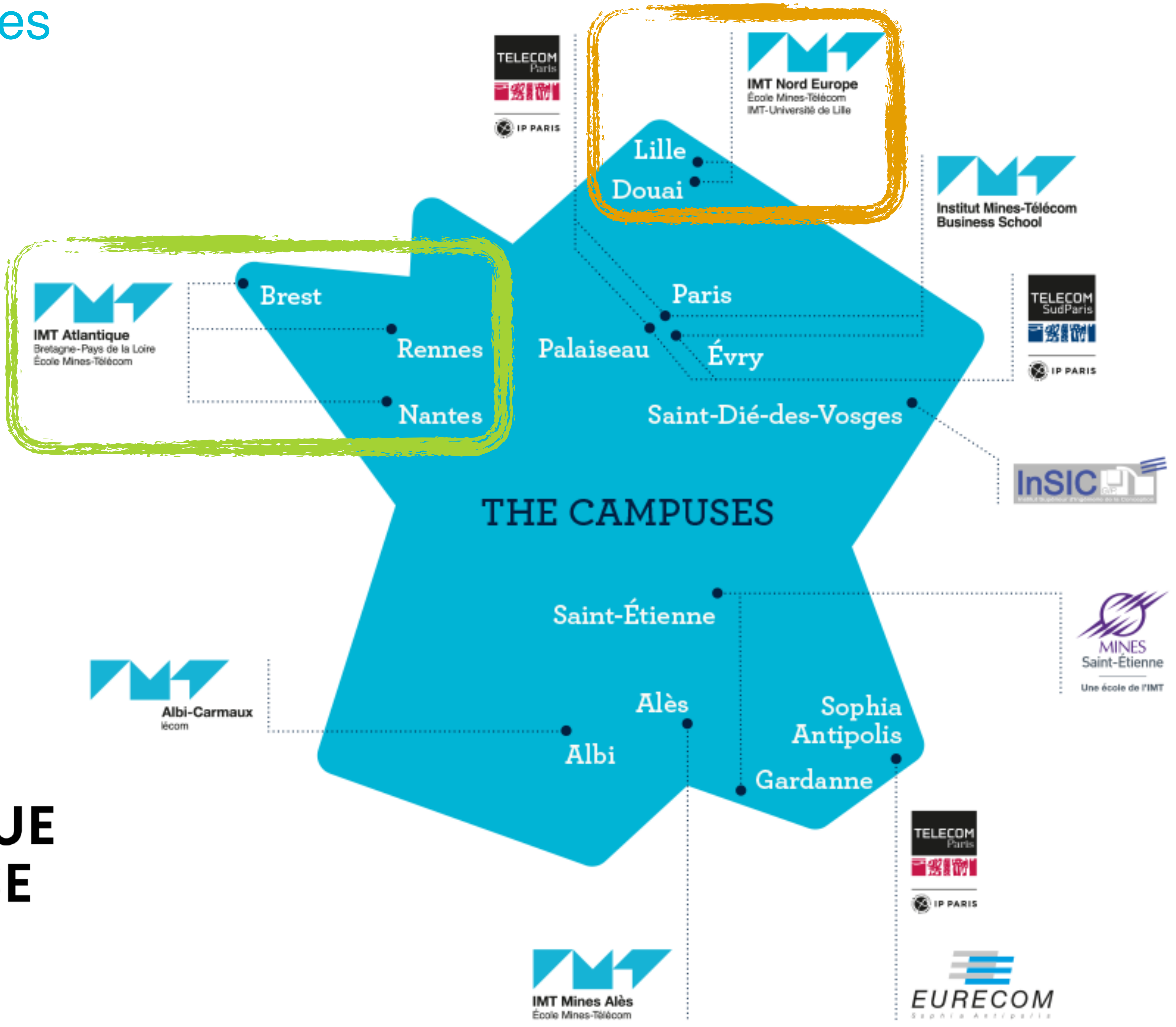
IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

UMR IRISA

WHAT IS IMT?

8 Technological Universities
2 Subsidiaries

Institut Mines-Télécom



RÉPUBLIQUE FRANÇAISE
Liberté
Égalité
Fraternité

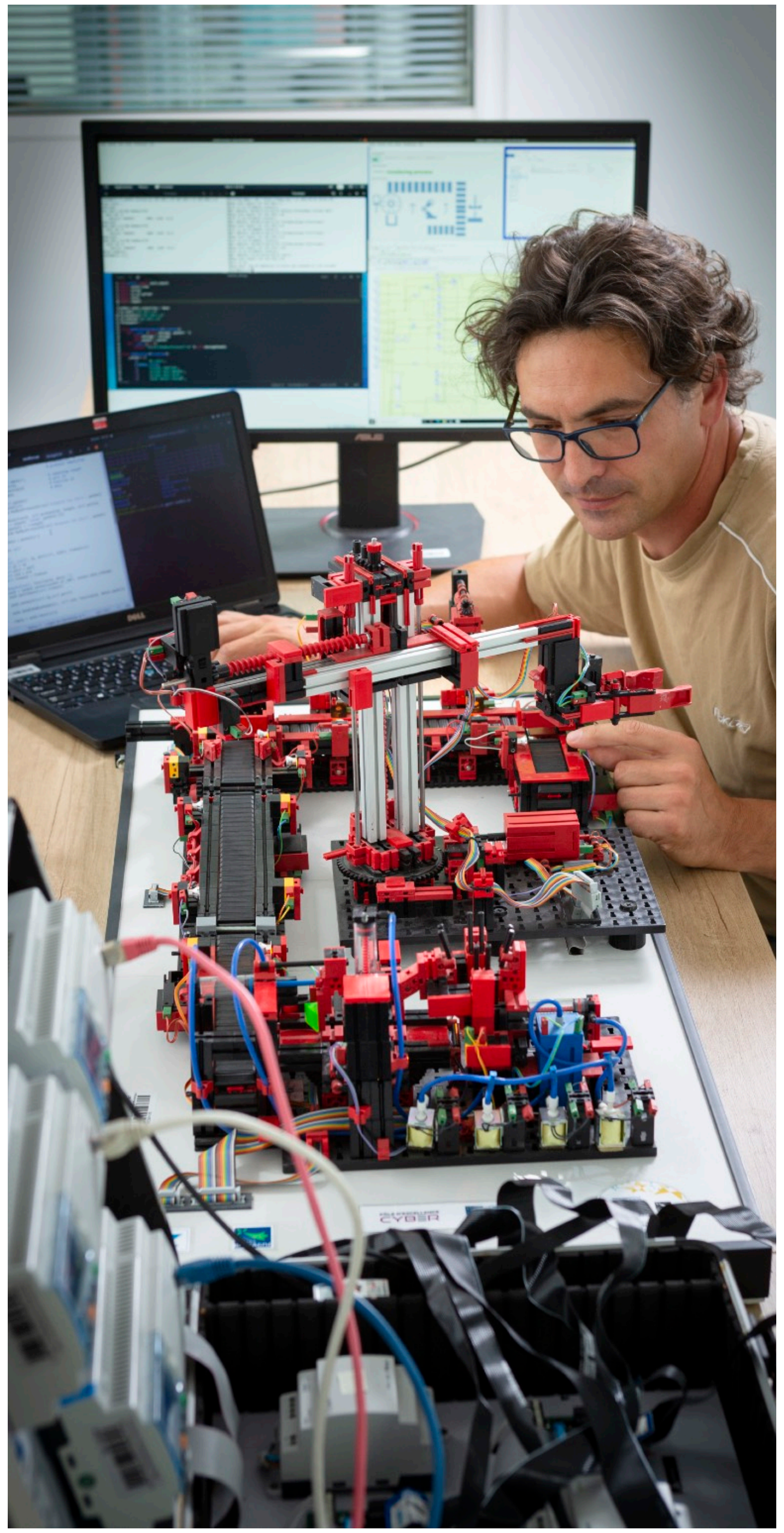
under the aegis of the Ministry of Industry and Digital Communications

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

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

UMR IRISA

RESEARCH PLATFORMS: CENCYBLE BUILDING AND REALISTIC TESTBEDS



LET'S TALK ABOUT FEDERATION

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

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

LET'S TALK ABOUT FEDERATION

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

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

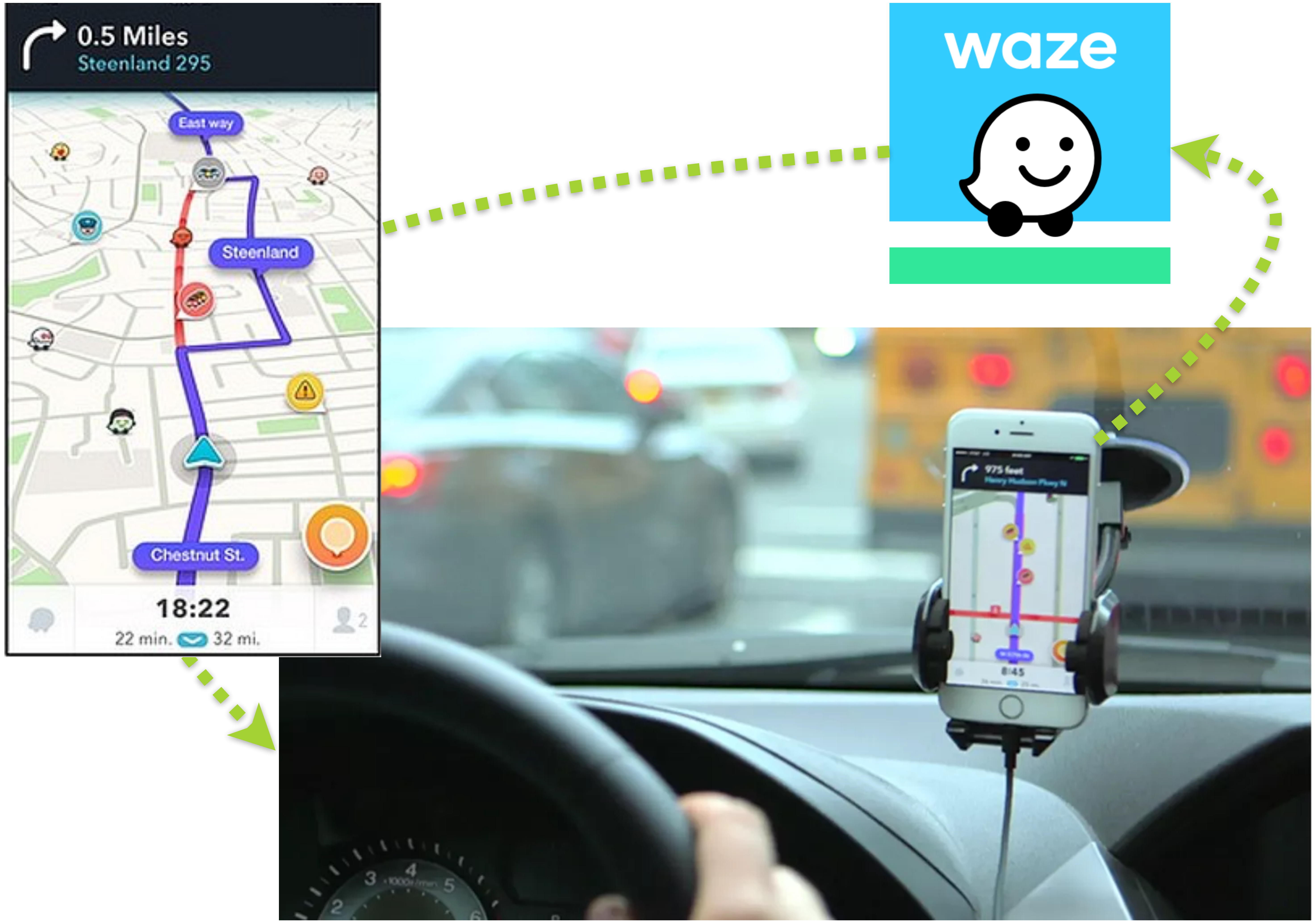
- « Large group of dispersed participants contributing or producing goods or services […] for payment or as volunteers »
  Wikipedia, 2023
- Waze Example

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

ALL START FROM CROWDSOURCING

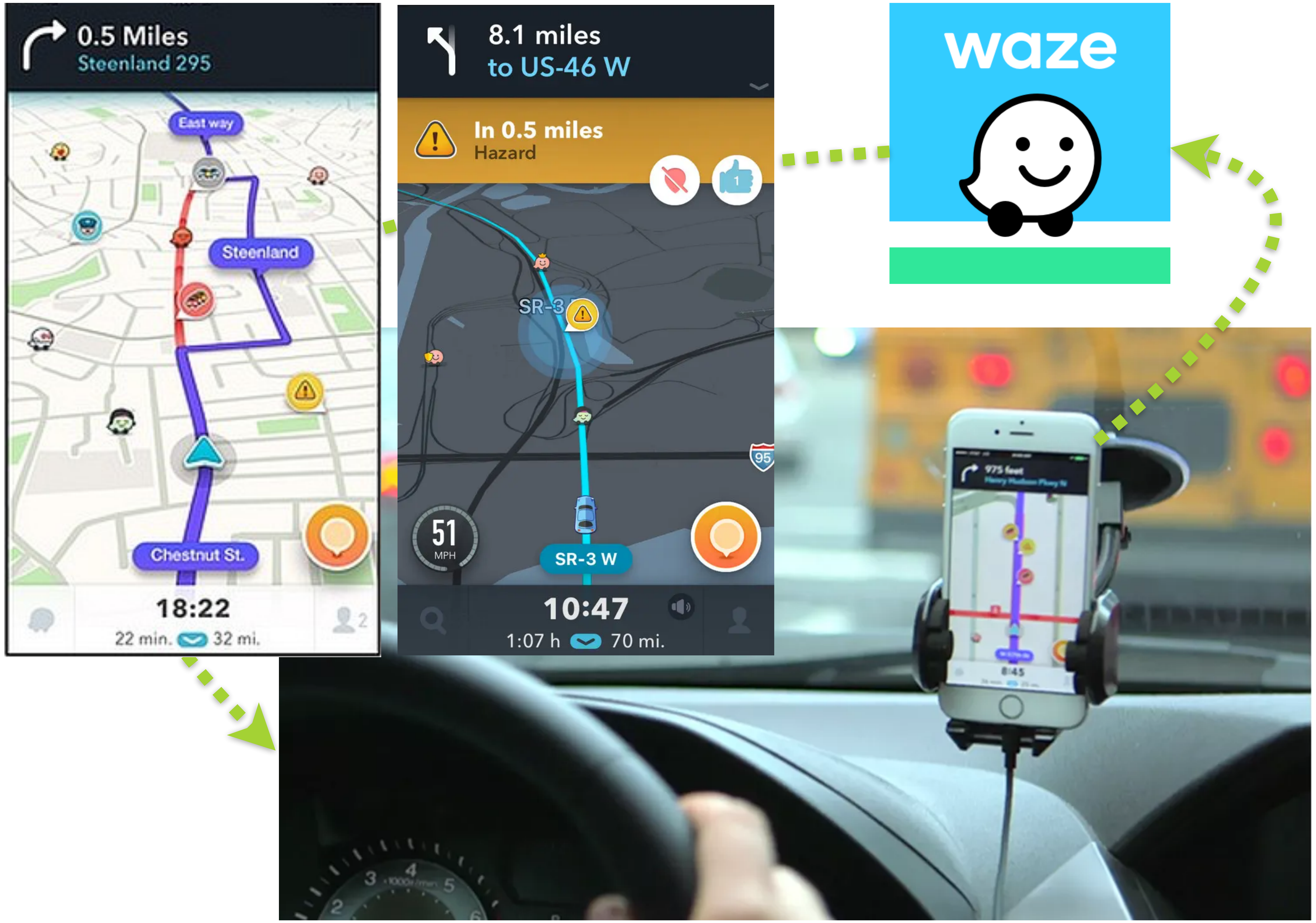
- **« Large group of dispersed participants contributing or producing goods or services […] for payment or as volunteers »**
  Wikipedia, 2023
- **Waze Example**

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



ALL START FROM CROWDSOURCING

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



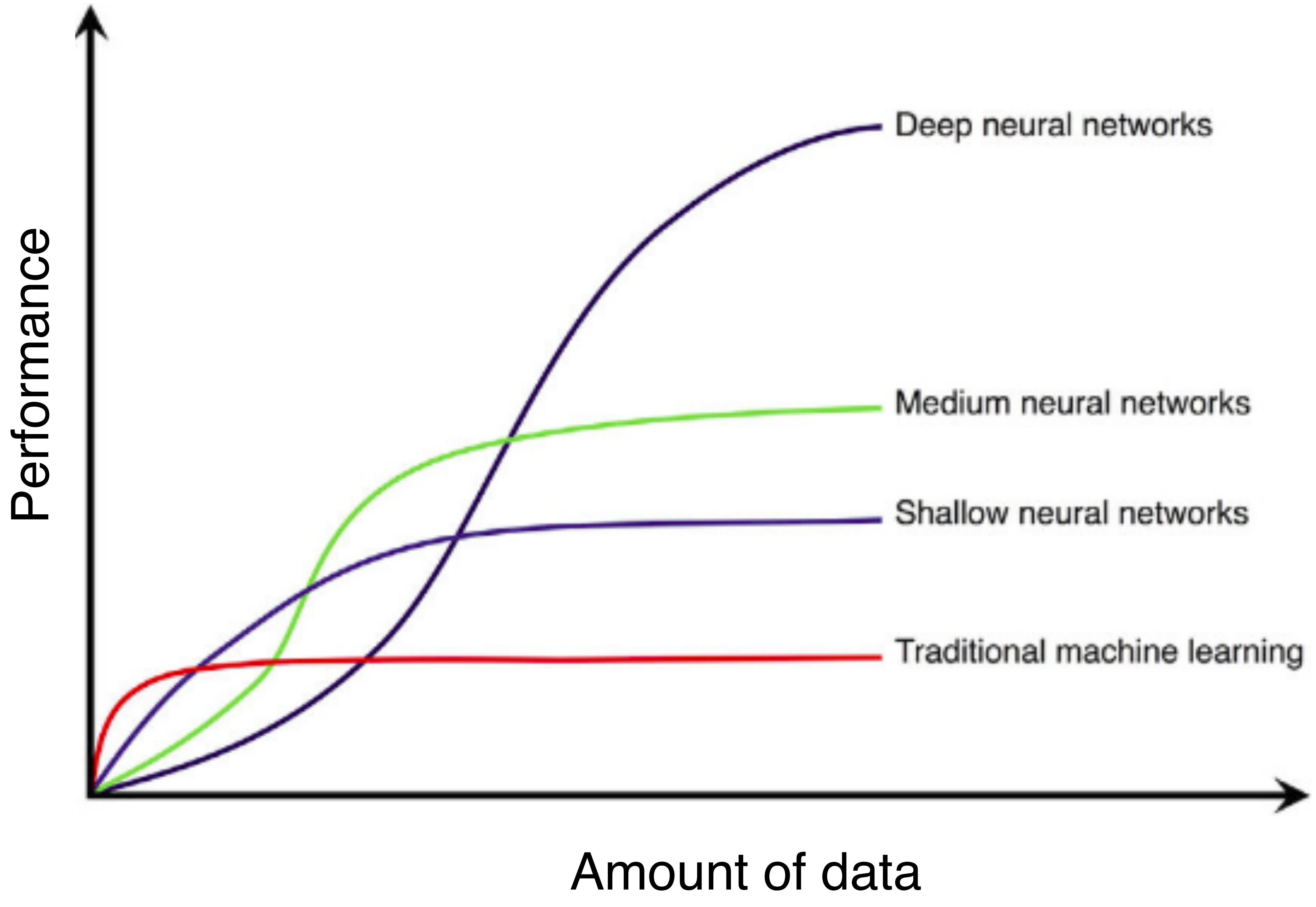
ALL START FROM CROWDSOURCING

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

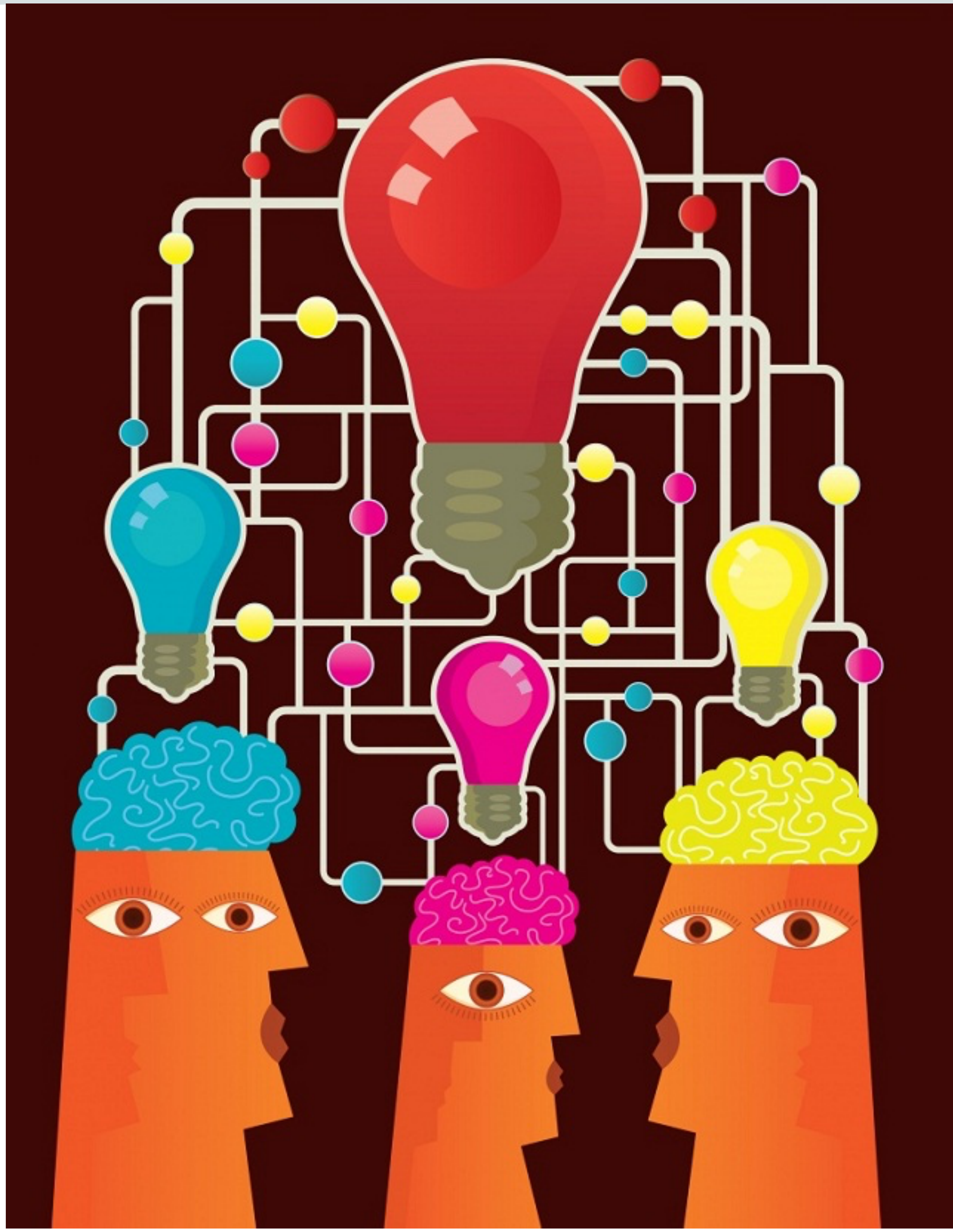
amazon
mechanical turk

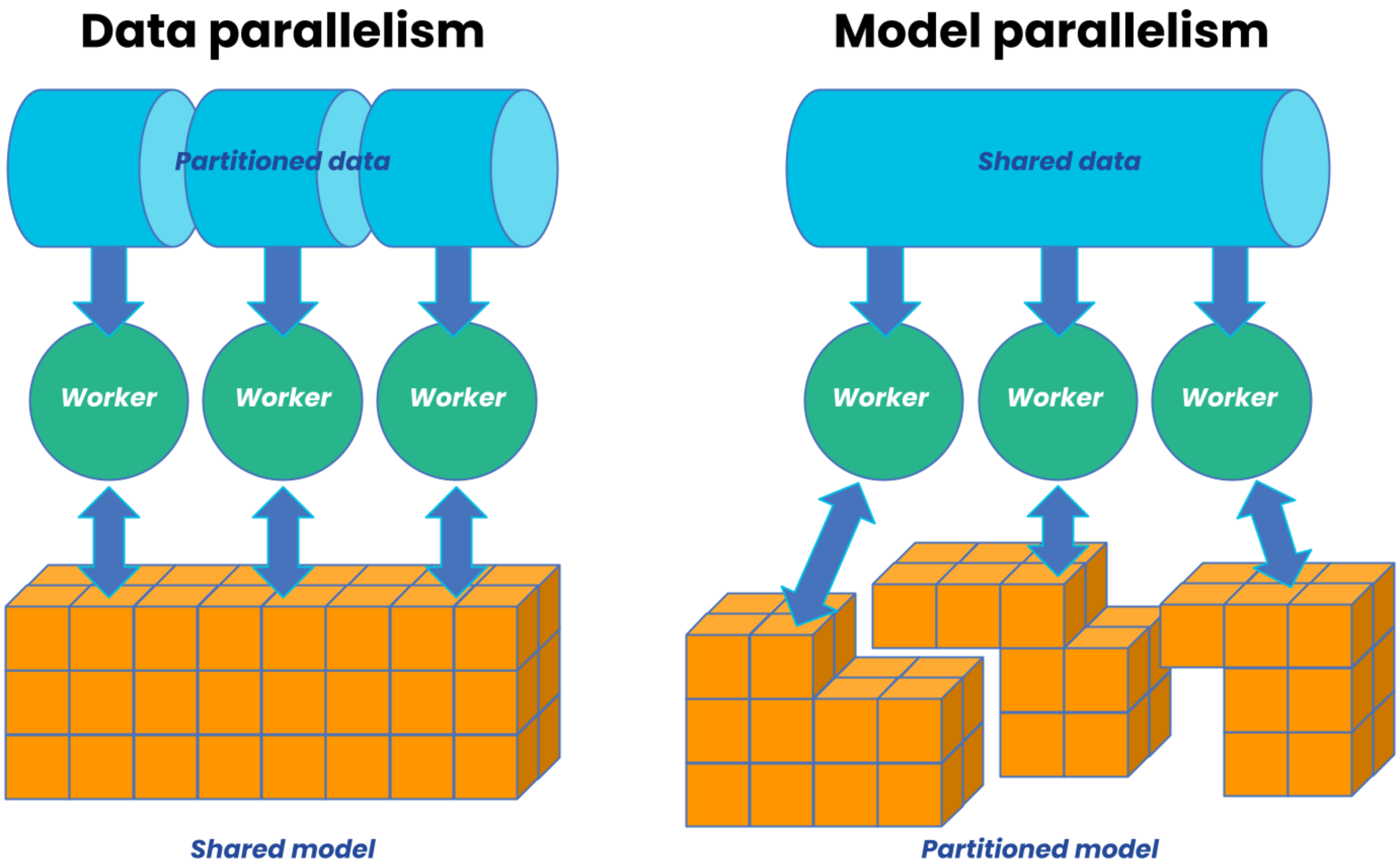
CloudResearch®
connect™

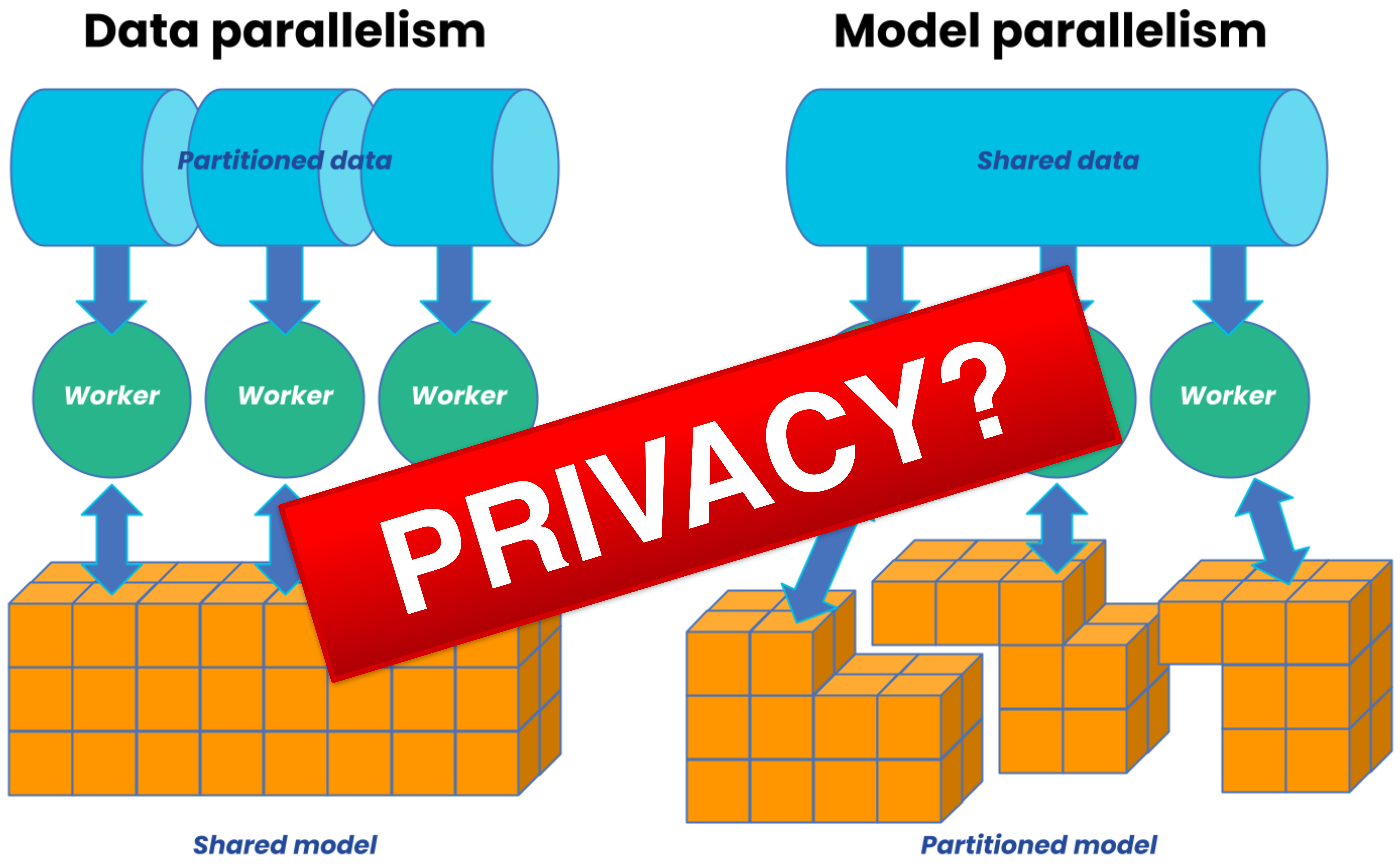
- **Performance improve with more data**
  - Increases accuracy
  - Scales to larger input data sizes
- **If computational complexity outpaces the main memory**
  - Not scale well due to memory restrictions



- **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**

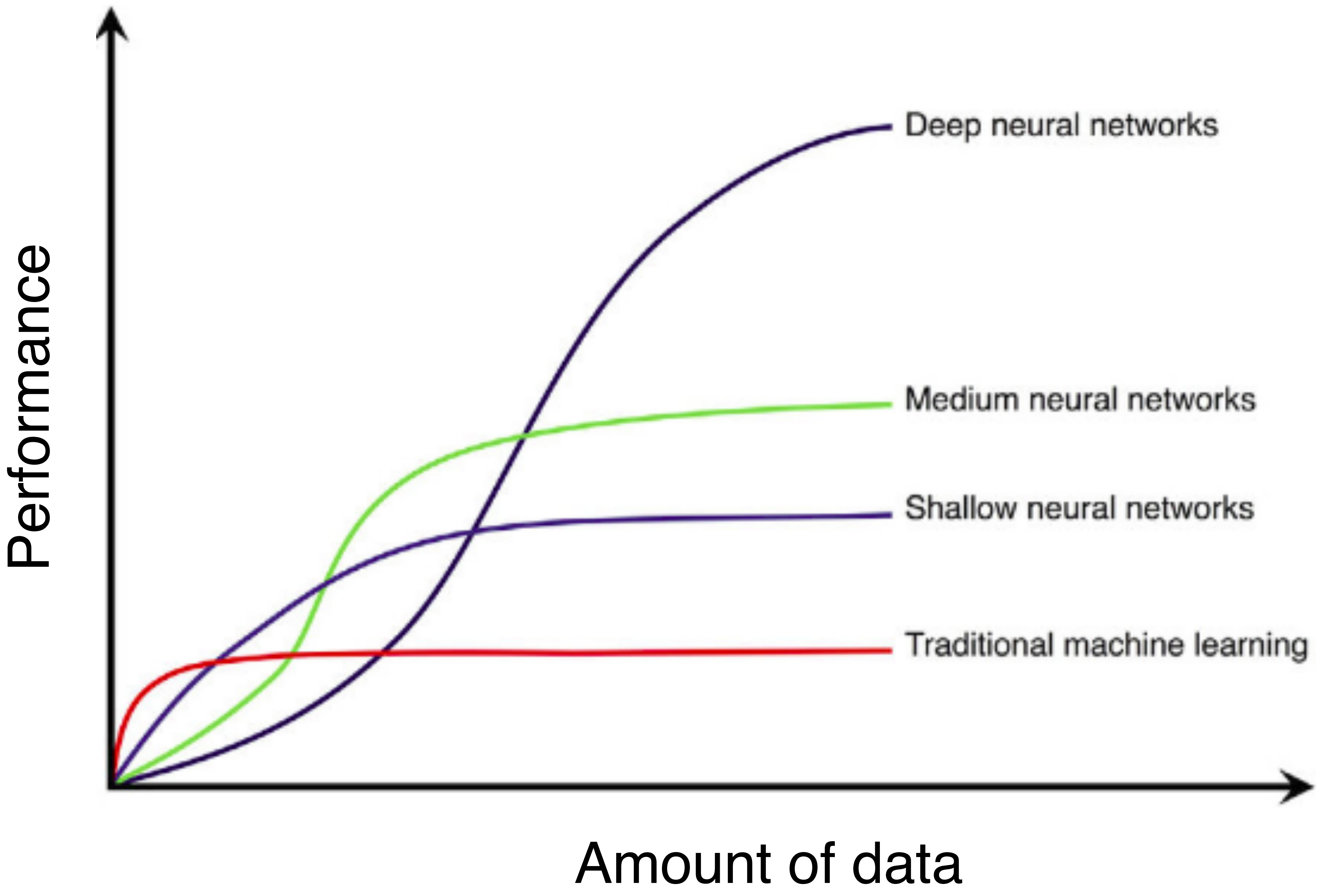



Data parallelism
Partitioned data
Worker
Worker
Worker
Shared model
Model parallelism
Shared data
Worker
Worker
Worker
Partitioned model


Data parallelism
Model parallelism
Partitioned data
Shared data
Worker
Worker
Worker
Worker
PRIVACY?
Shared model
Partitioned model

- **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

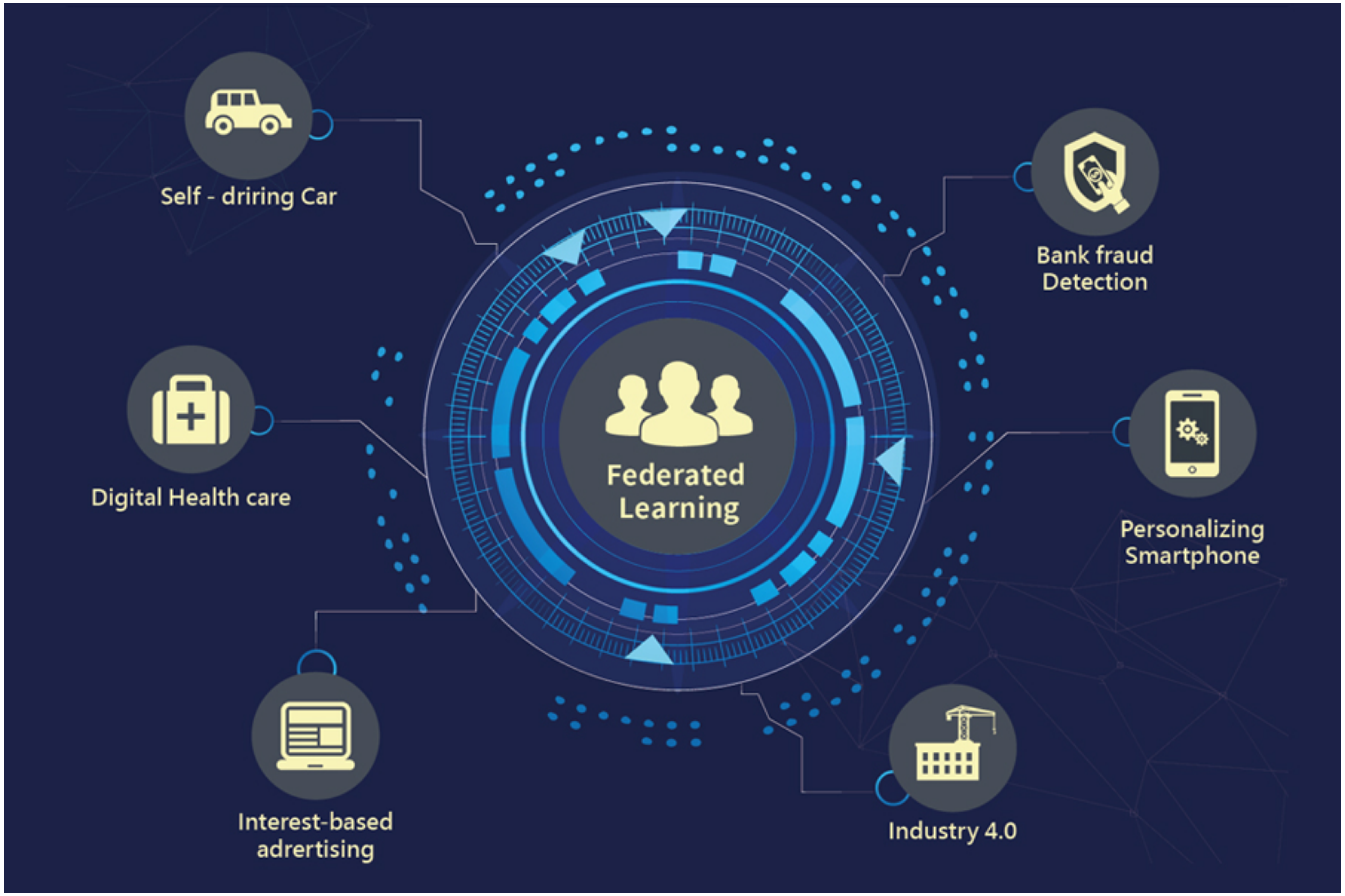


FEDERATED LEARNING IN A NUTSHELL

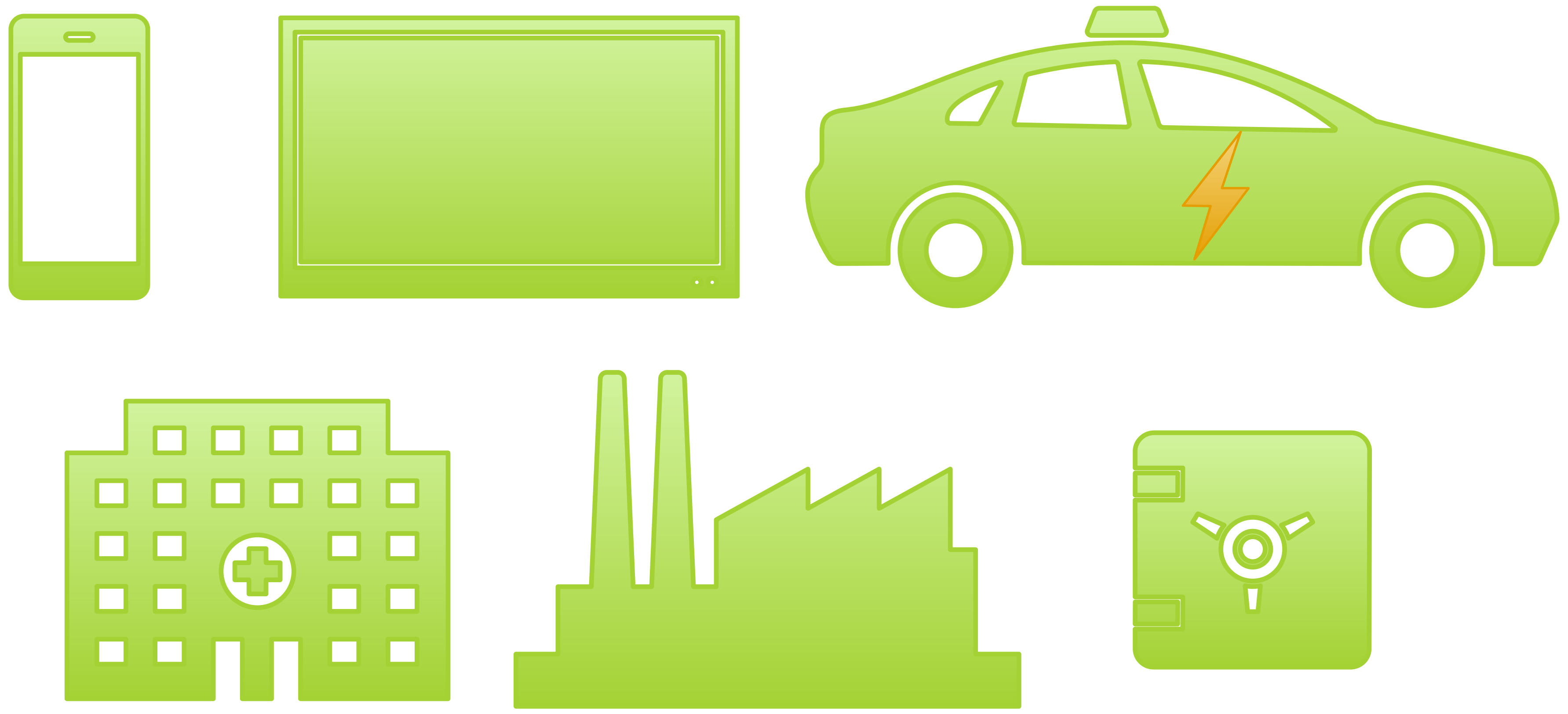
IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

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

FEDERATED LEARNING (FL) APPROACH

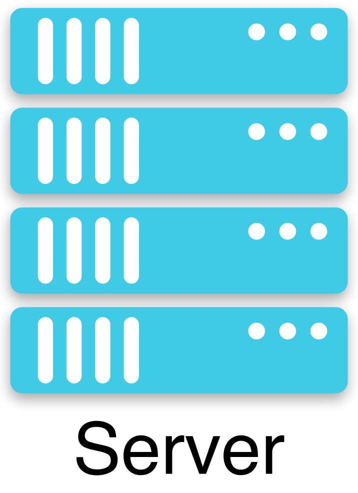


- **Multiple participants**
  - Contributes individually
- **All sort of devices**
  - Users' interaction data
  - Enough processing power

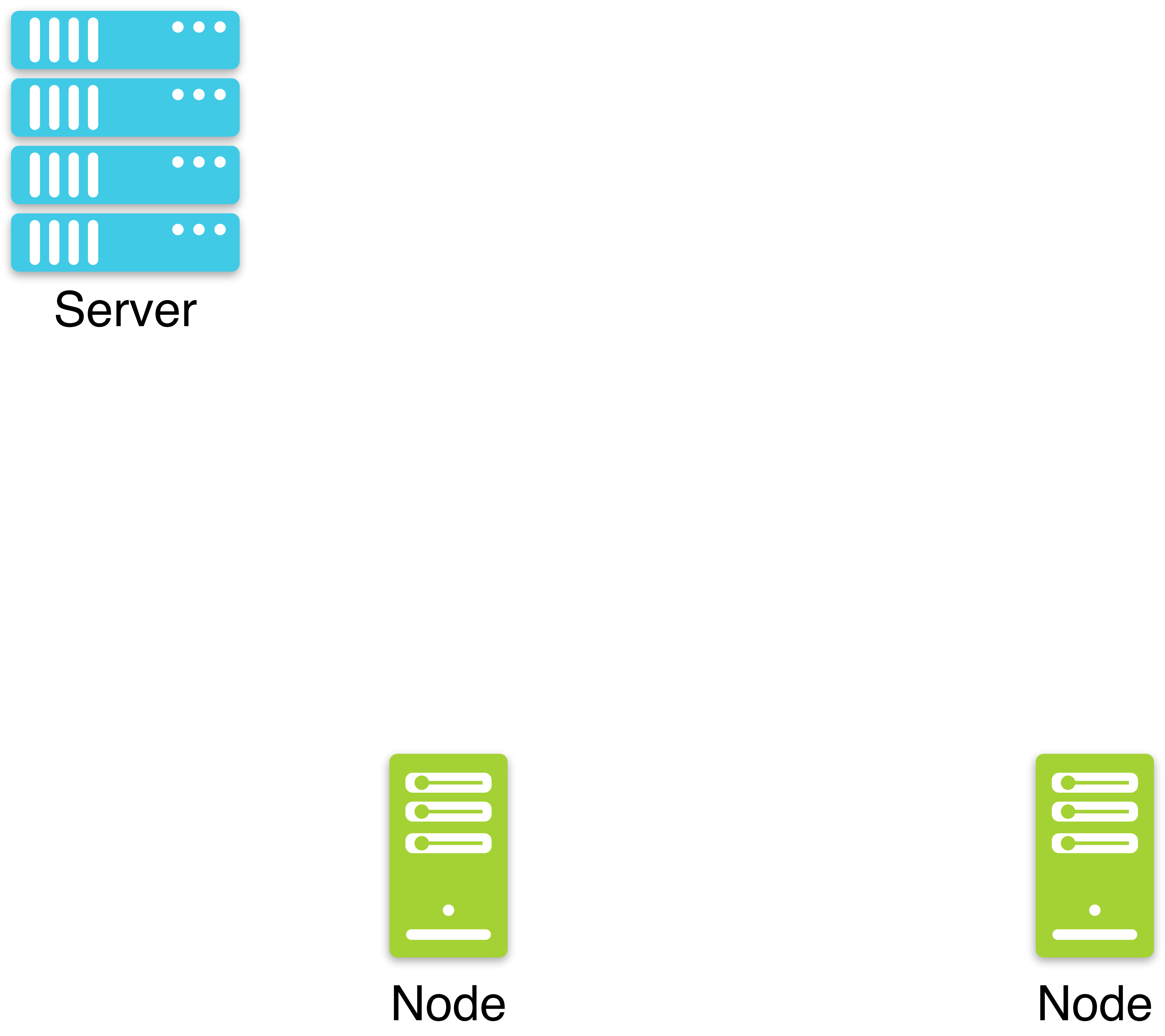


- A network of nodes shares *models* rather than *training data* with the server

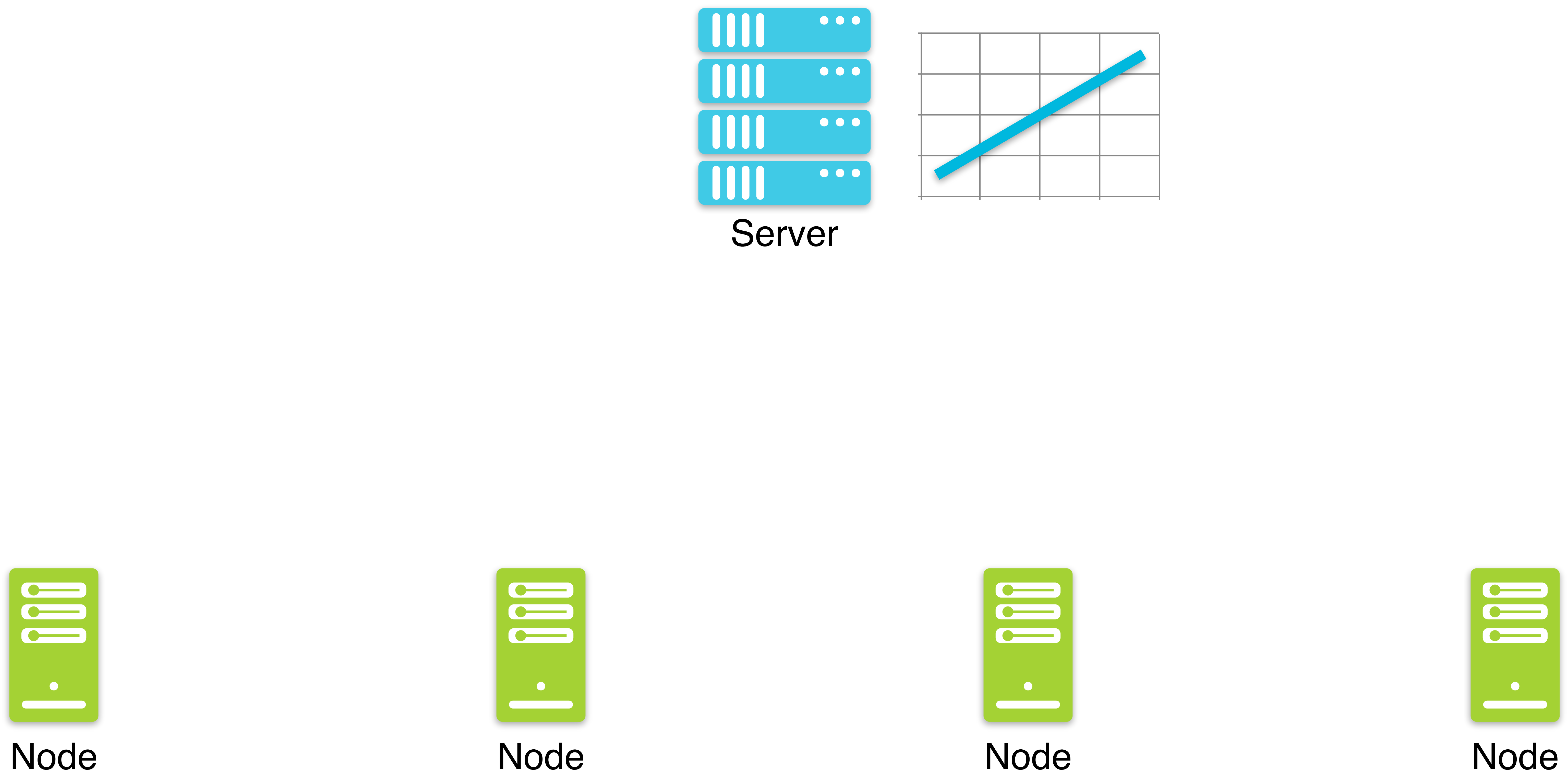
- **A network of nodes shares *models* rather than *training data* with the server**



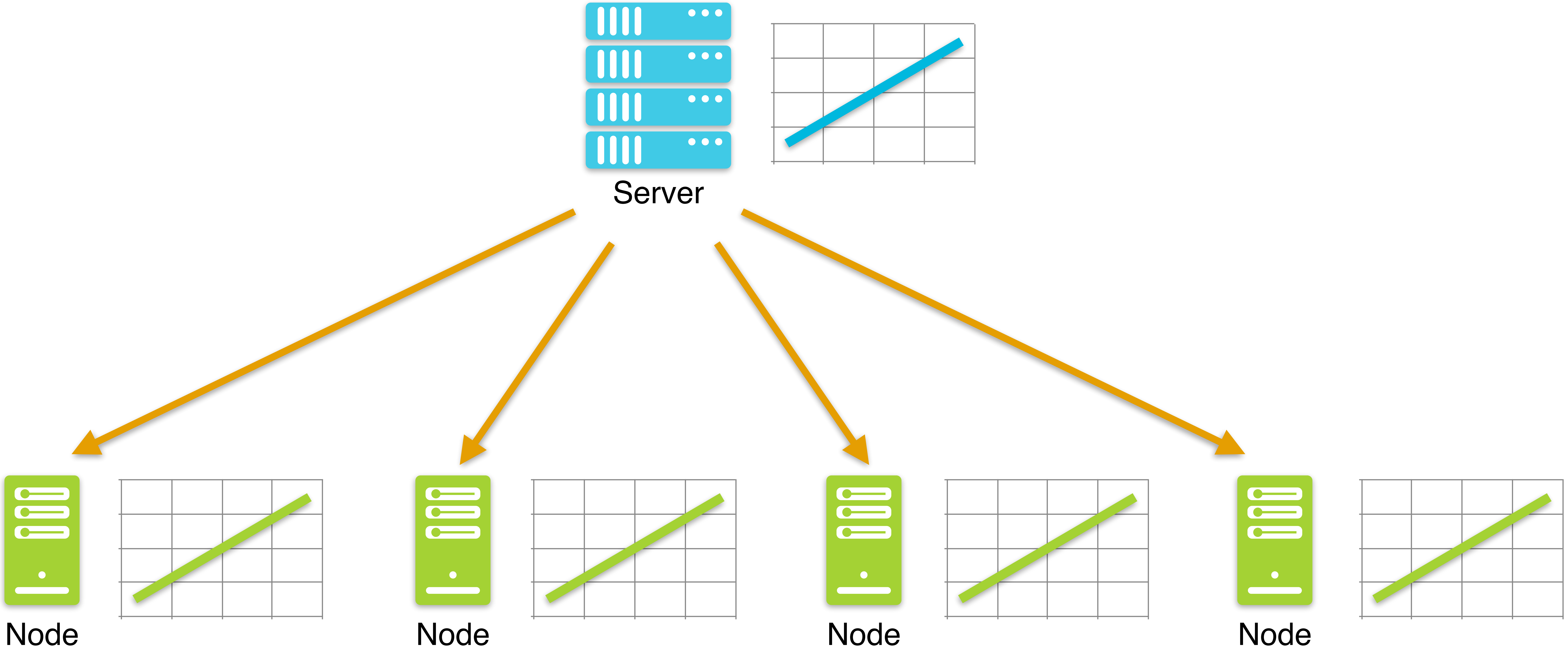
- A network of nodes shares *models* rather than *training data* with the server



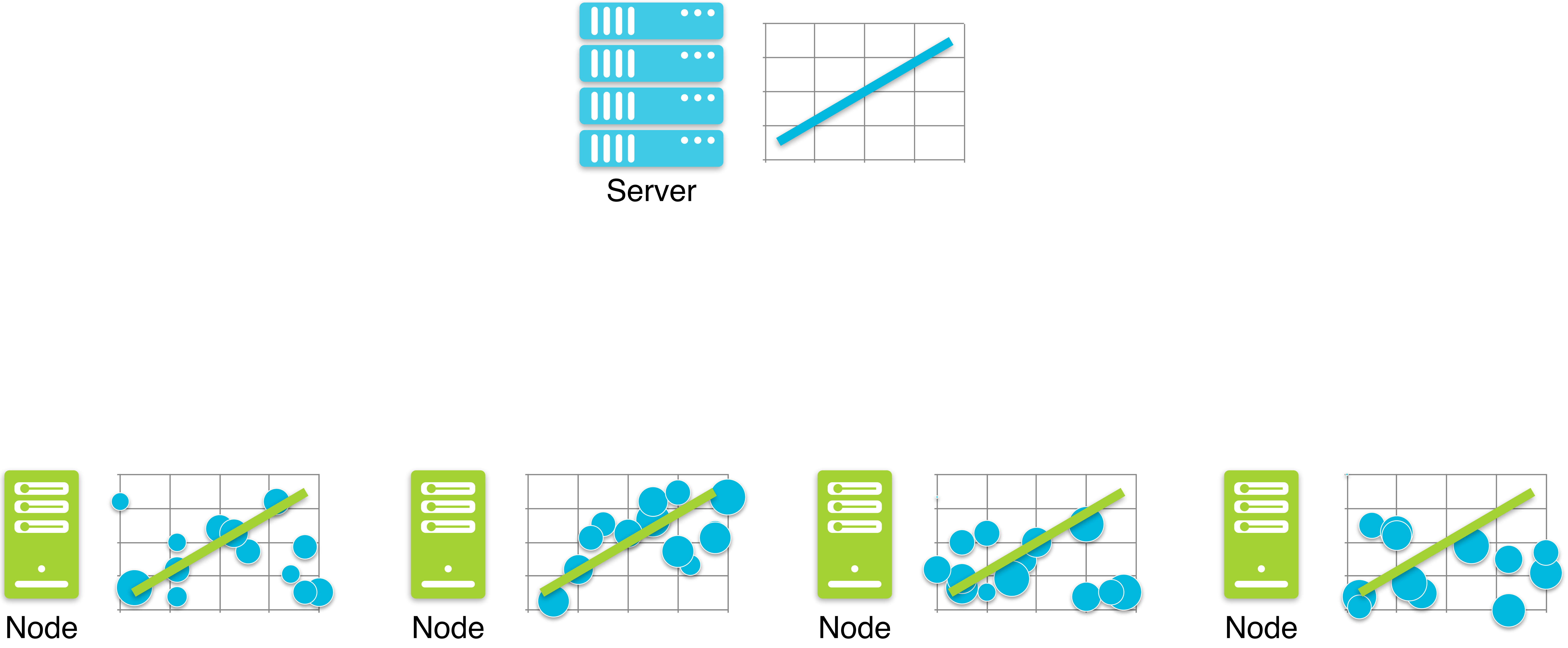
- **A network of nodes shares *models* rather than *training data* with the server**



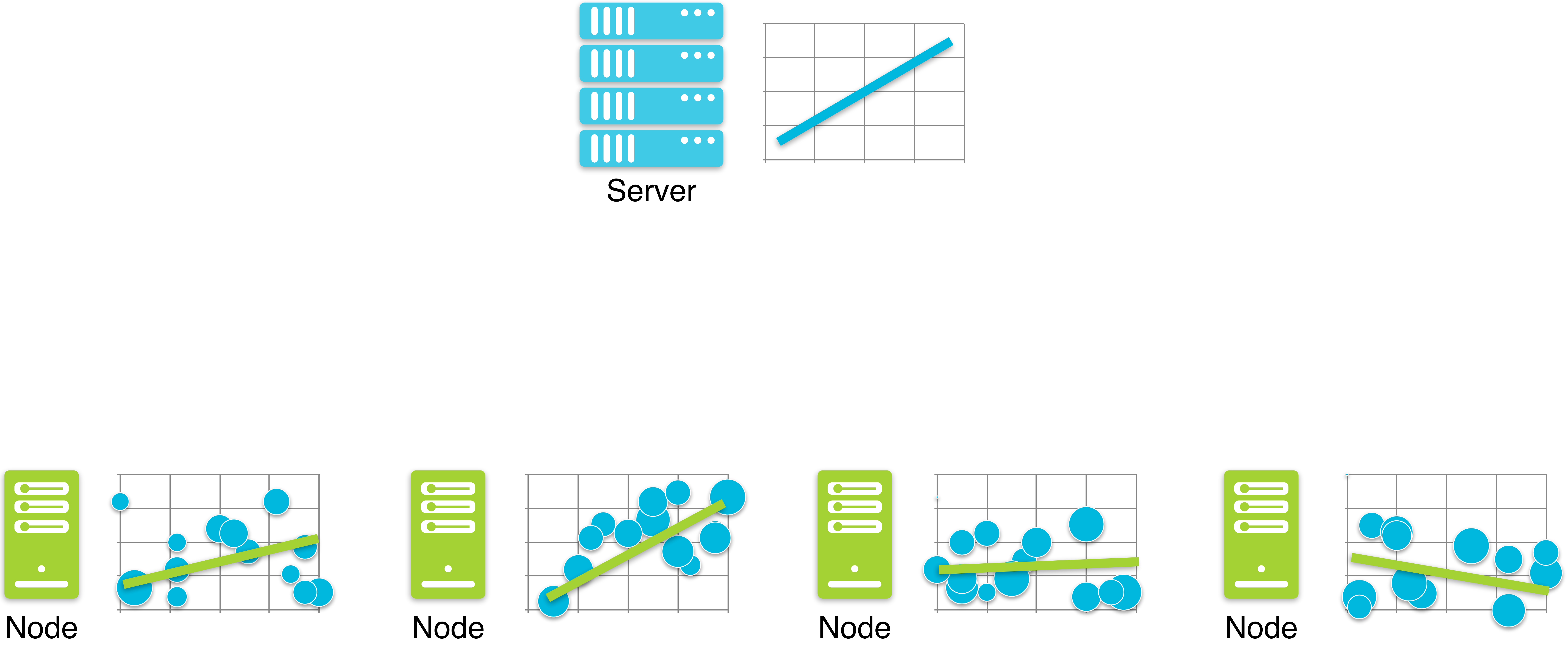
- A network of nodes shares *models* rather than *training data* with the server



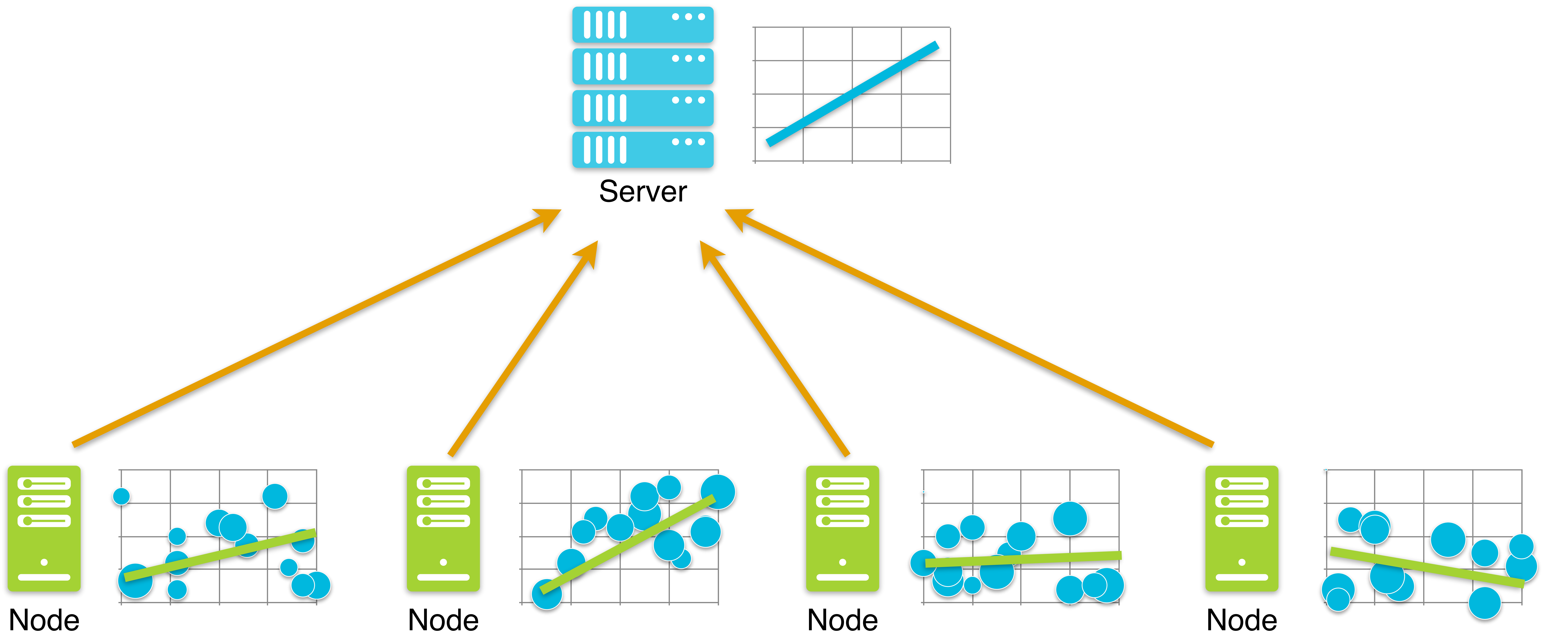
- A network of nodes shares *models* rather than *training data* with the server



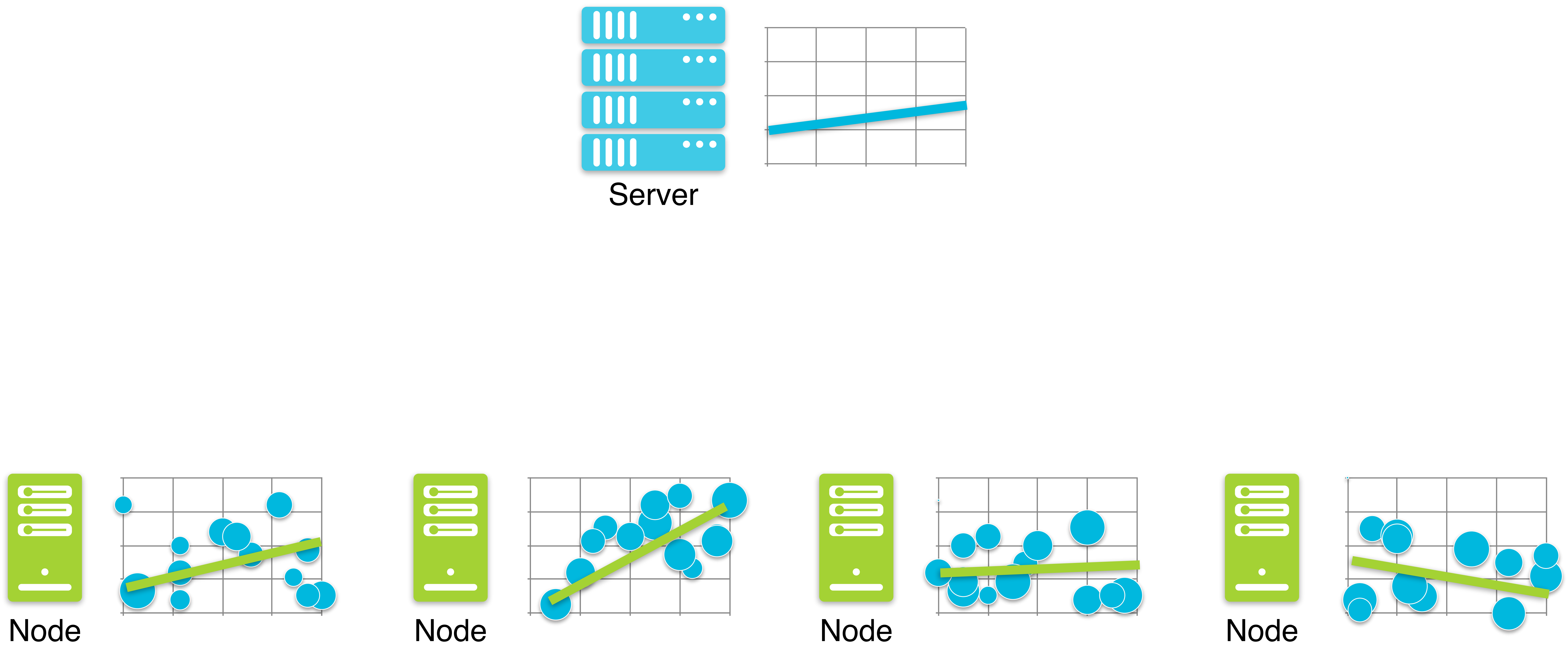
- A network of nodes shares *models* rather than *training data* with the server



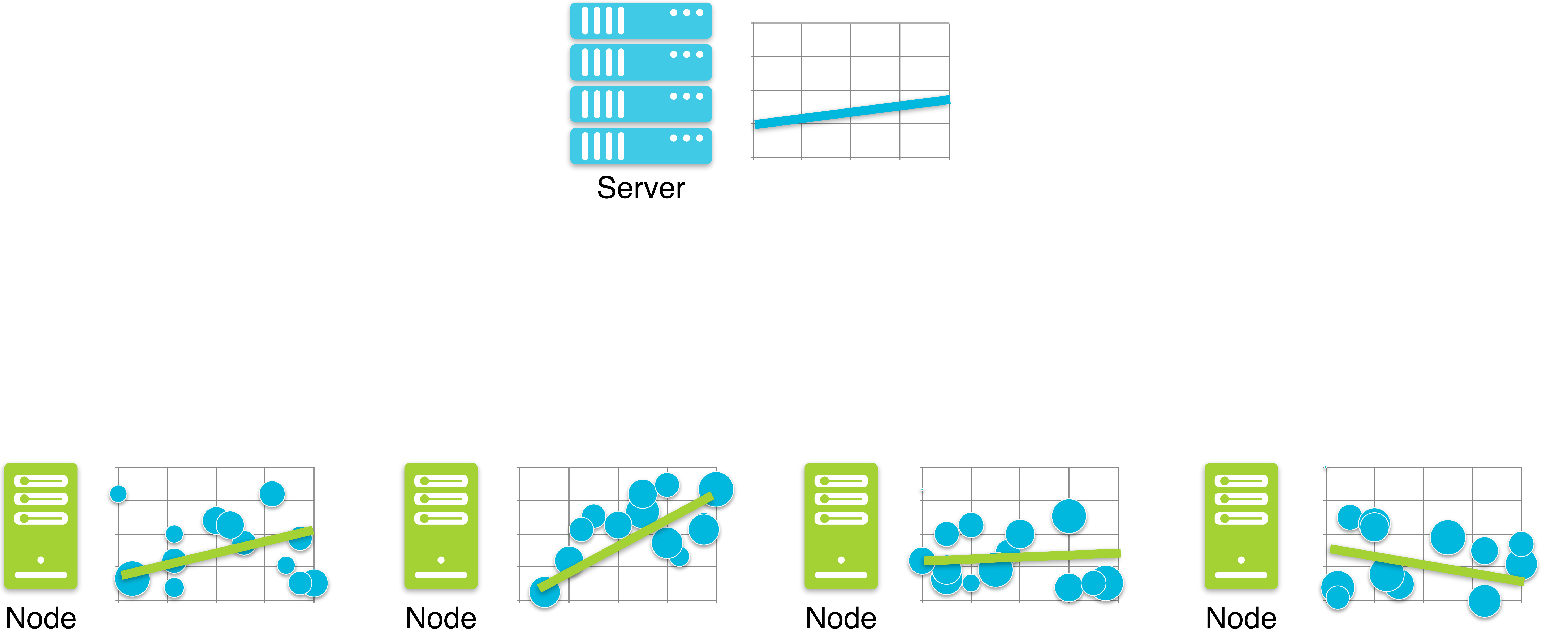
- A network of nodes shares *models* rather than *training data* with the server



- A network of nodes shares *models* rather than *training data* with the server

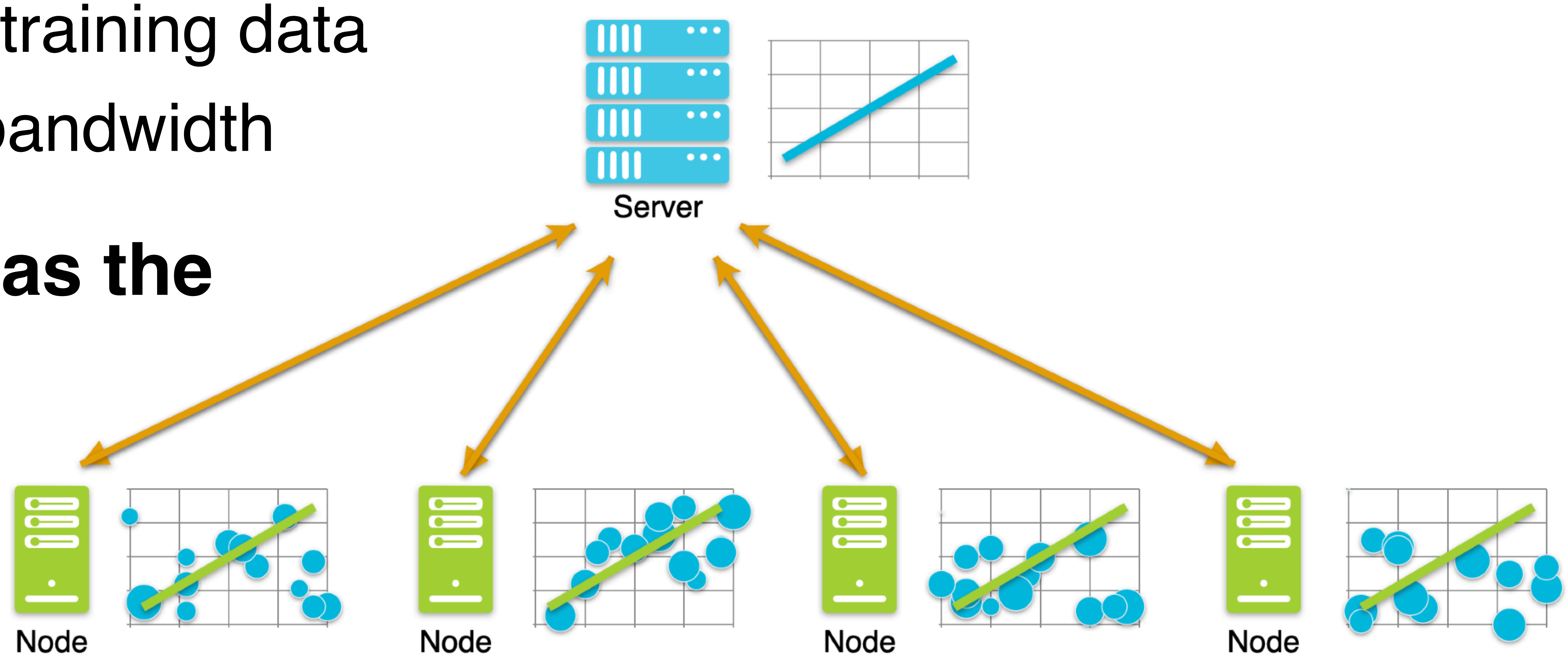


- A network of nodes shares *models* rather than *training data* with the server

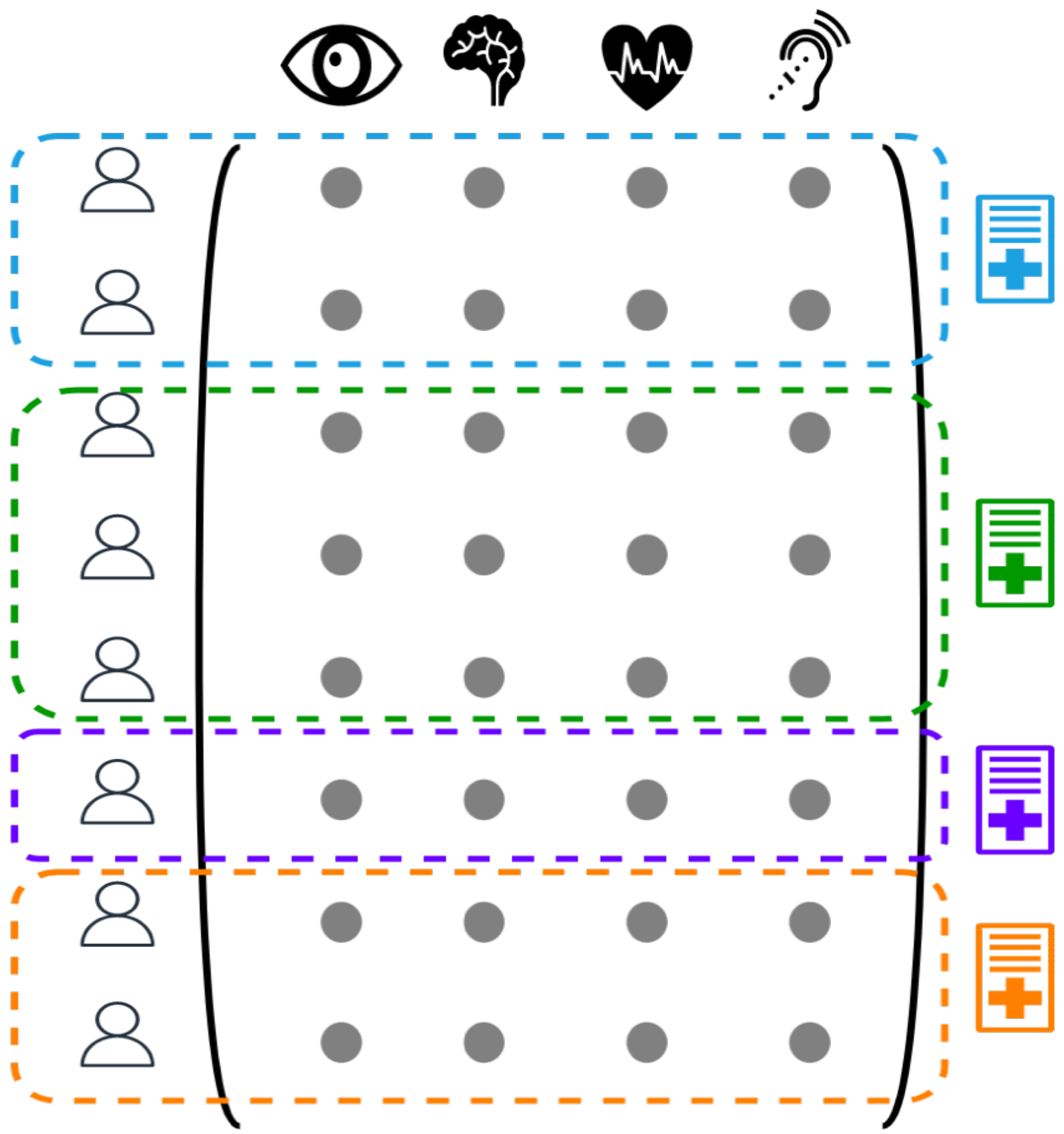


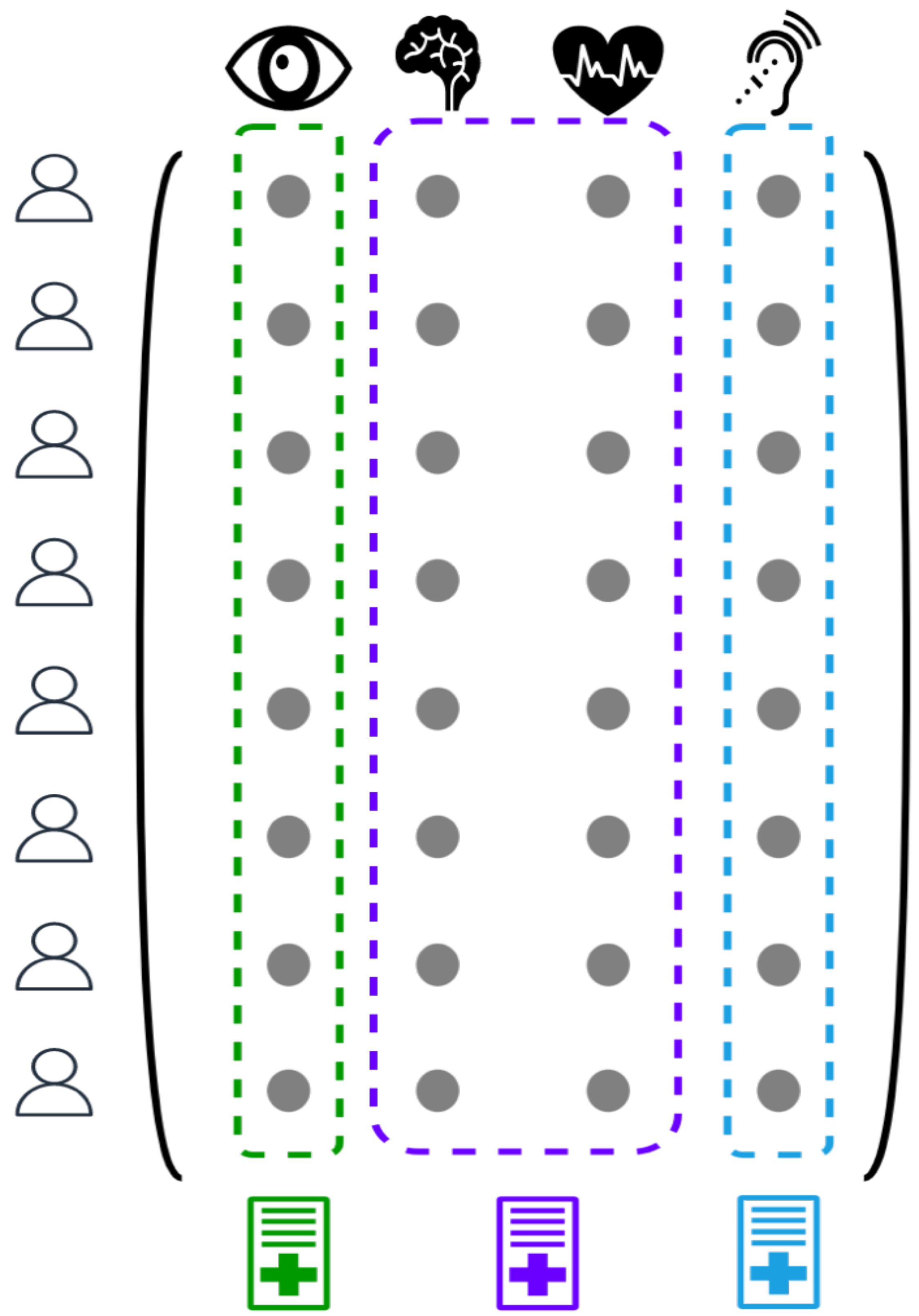
- We repeat the whole process many times

- **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



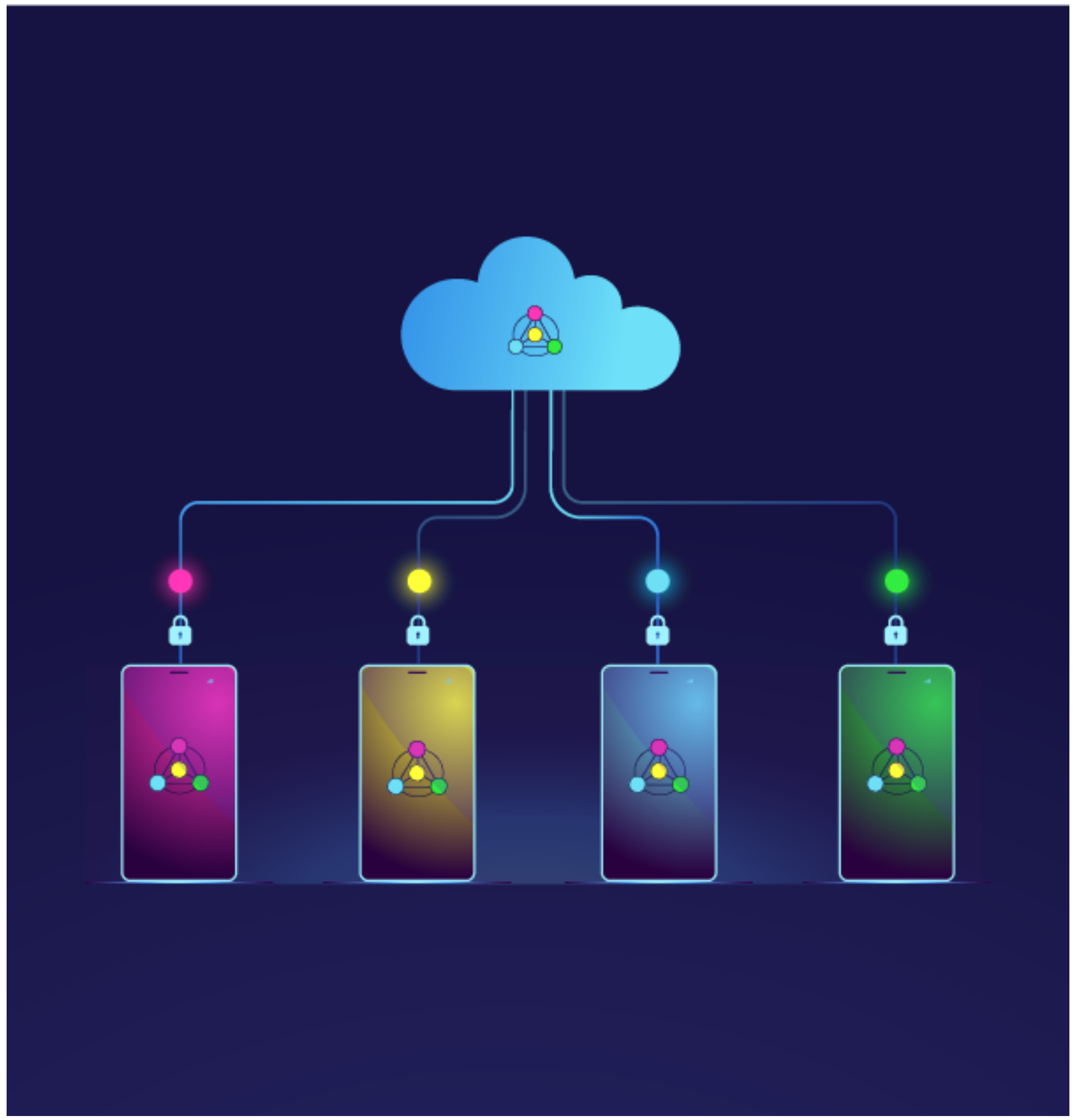
DIFFERENT TYPE OF FEDERATED LEARNING





- **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

- **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**



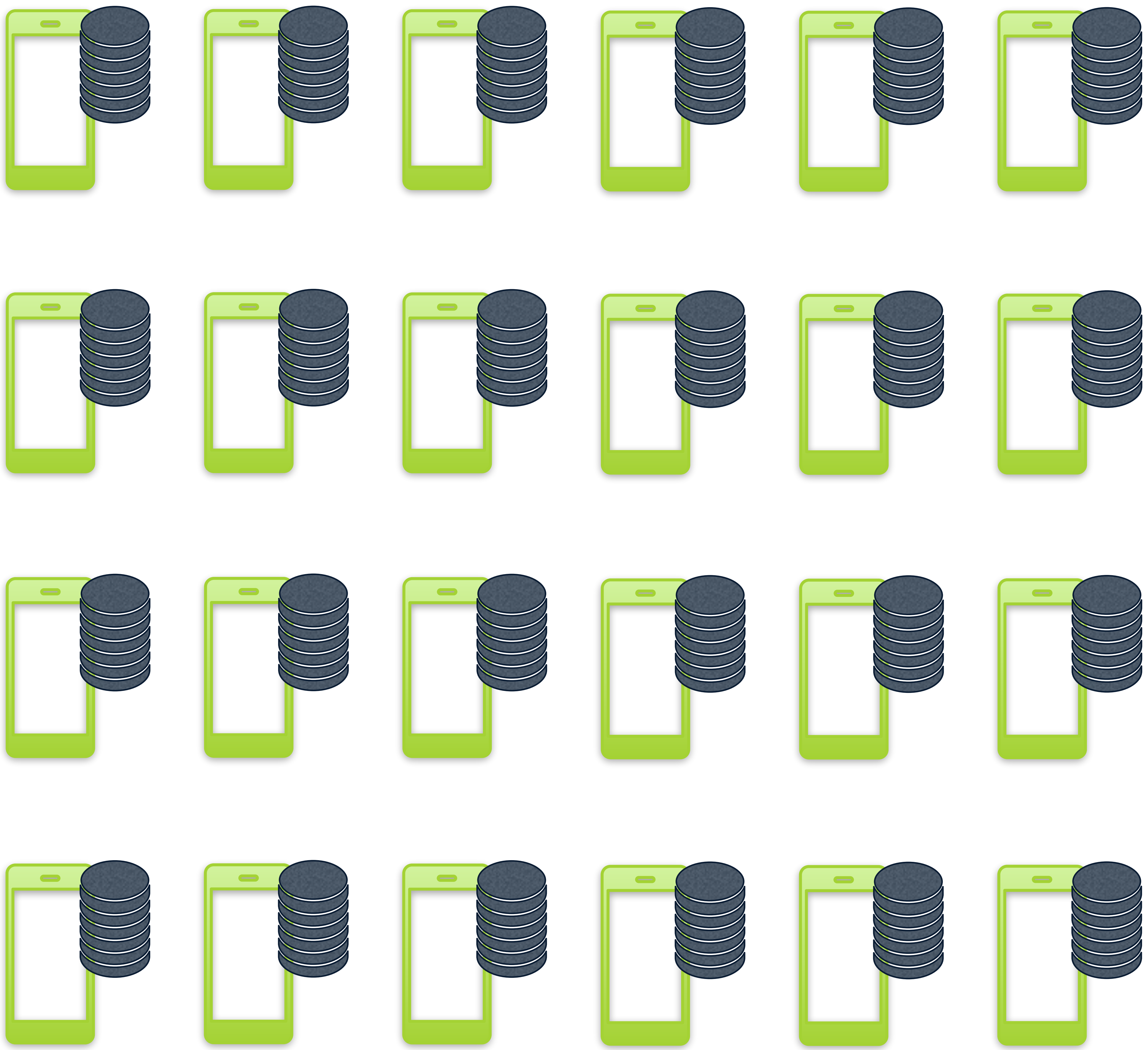
EXAMPLE WITH FEDAVG (FEDERATED AVERAGING)

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

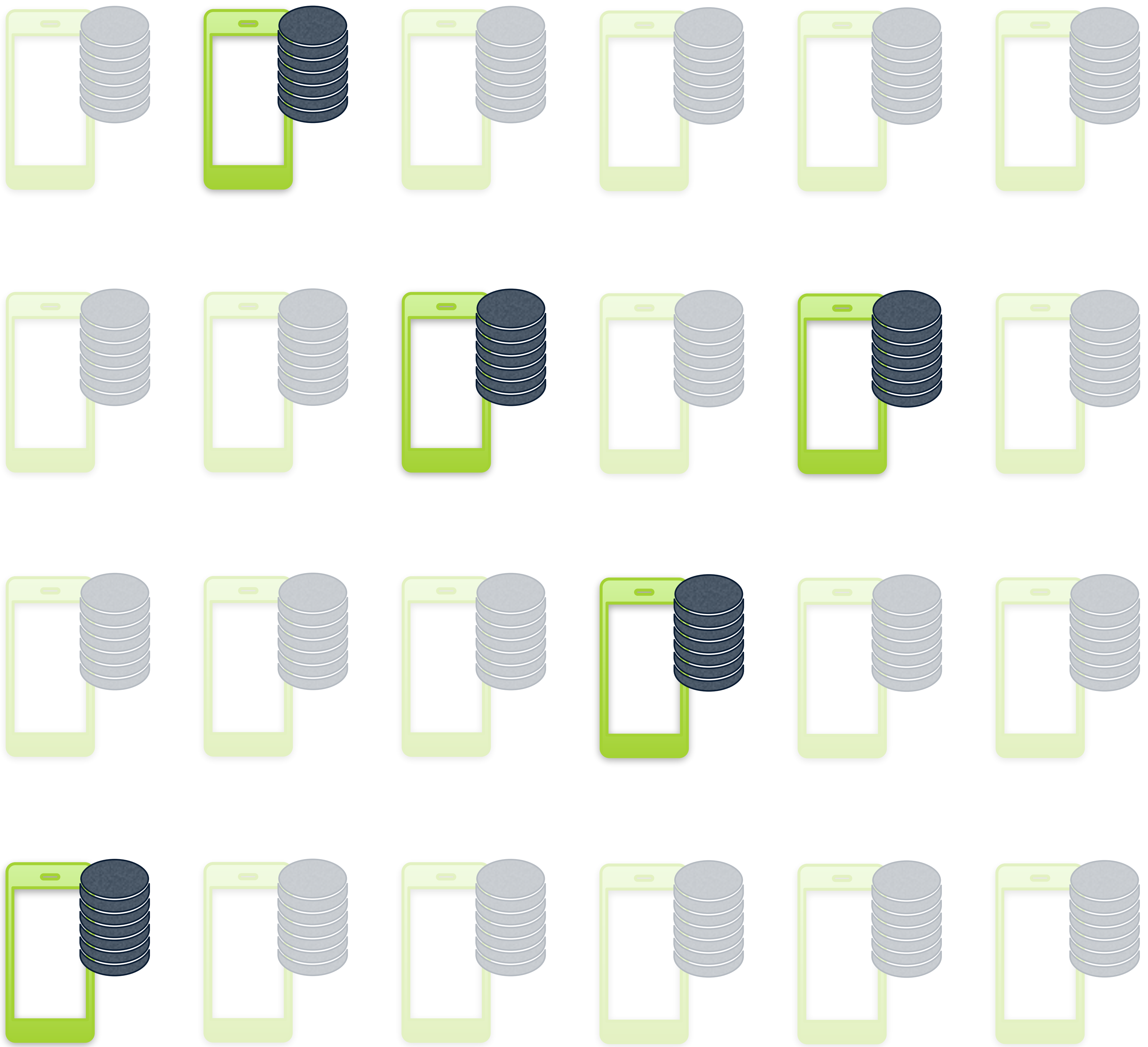
IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

- **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**

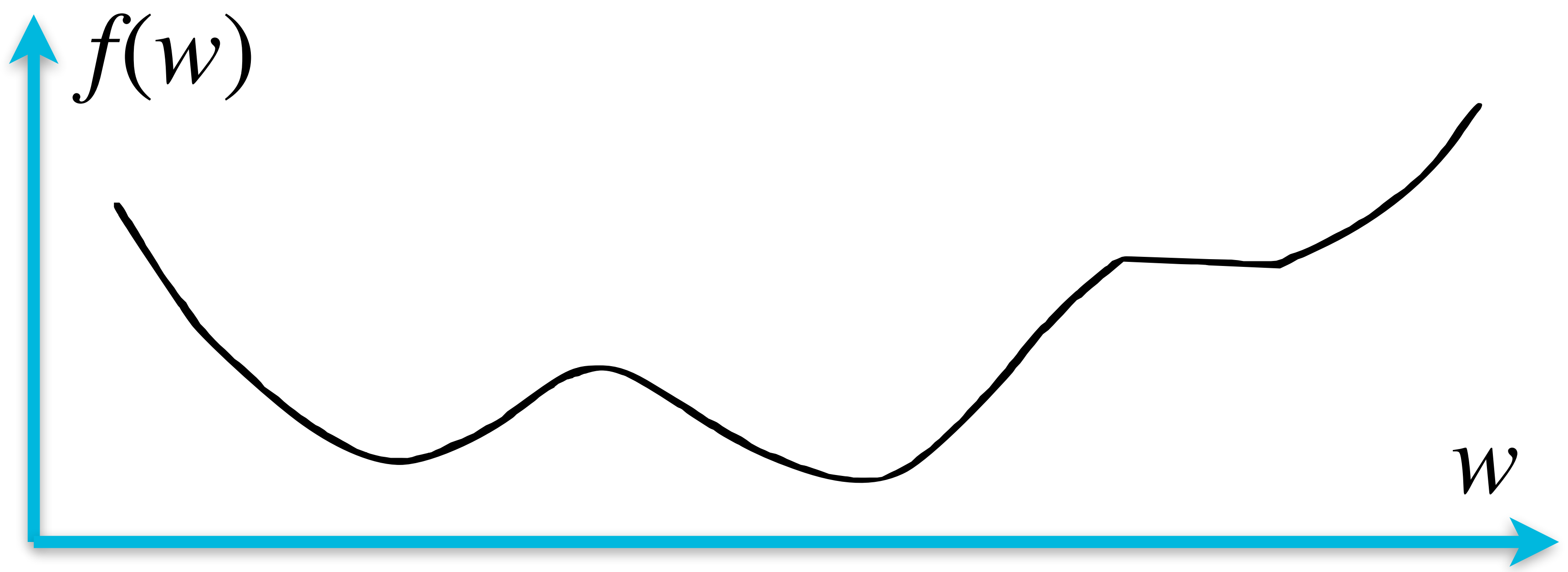
- **From a pool of candidates**
  - Chooses a subset of *eligible* participants
    - fully charged
    - specific hardware configurations
    - connected to a reliable and free WiFi network
    - idle
- **Not all devices participate in the federation**

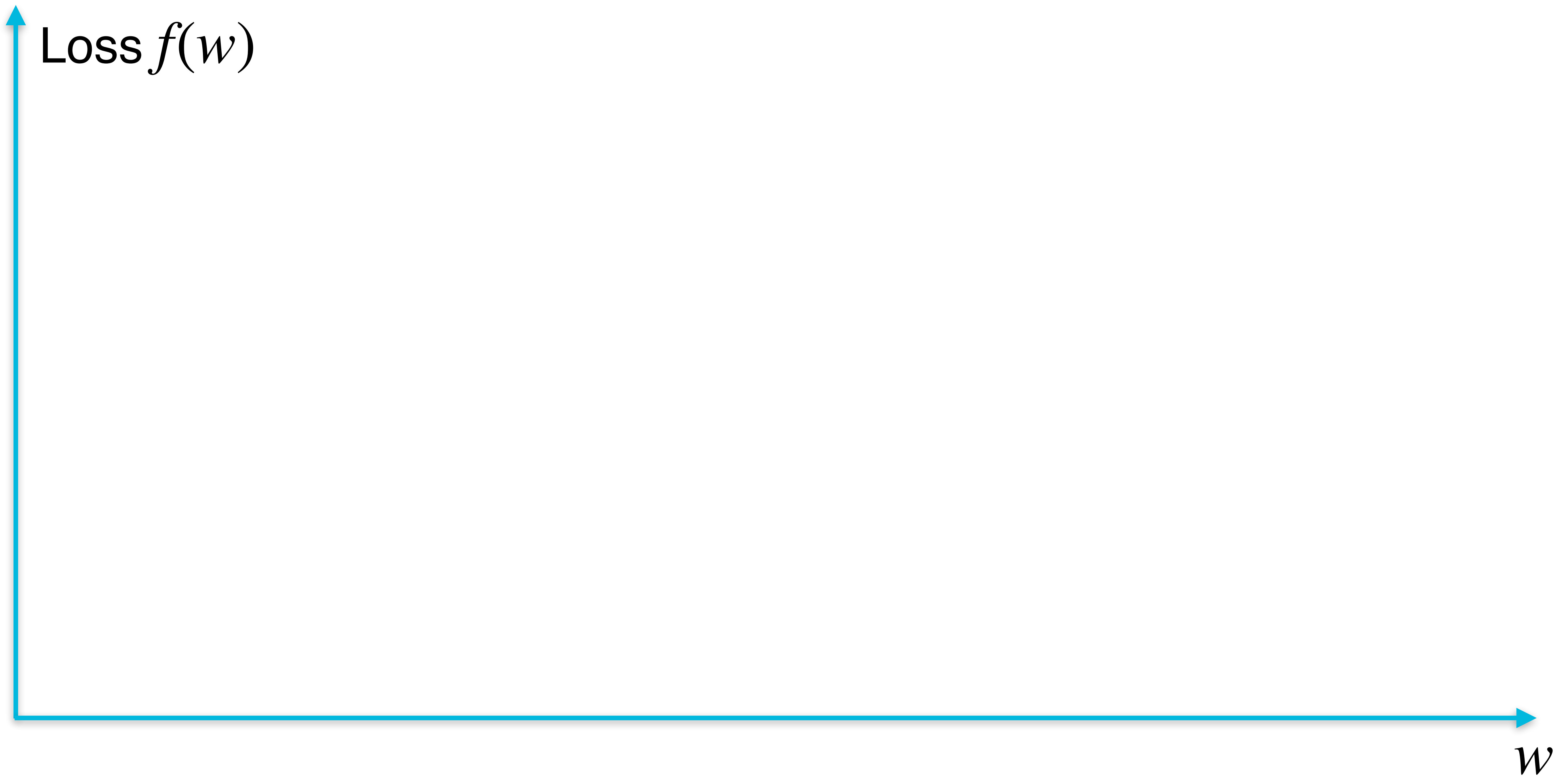


- **From a pool of candidates**
  - Chooses a subset of *eligible* participants
    - fully charged
    - specific hardware configurations
    - connected to a reliable and free WiFi network
    - idle
- **Not all devices participate in the federation**

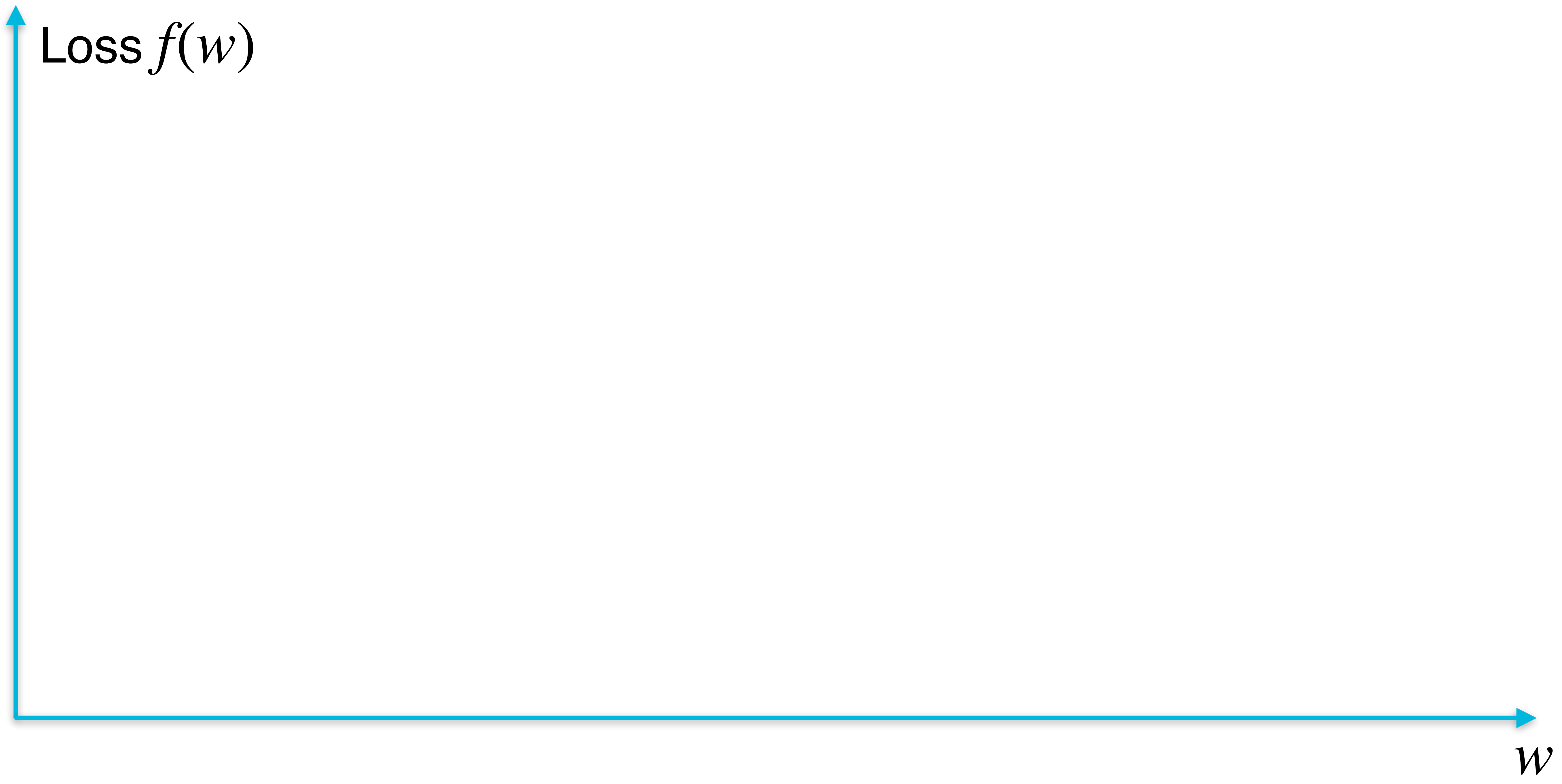


- **For a training dataset containing n samples $(x_i, y_i)_{1 \leq i \leq n}$, the training objective is**
  - $\min_{w \in \mathbb{R}^d} f(w)$ where $f(w) = \frac{1}{n} \sum_{i=1}^{n} f_i(w)$
  - with $f_i(w) = l(x_i, y_i, w)$, the loss of the prediction on example (x_i, y_i)
- **Properties**
  - Non-convex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

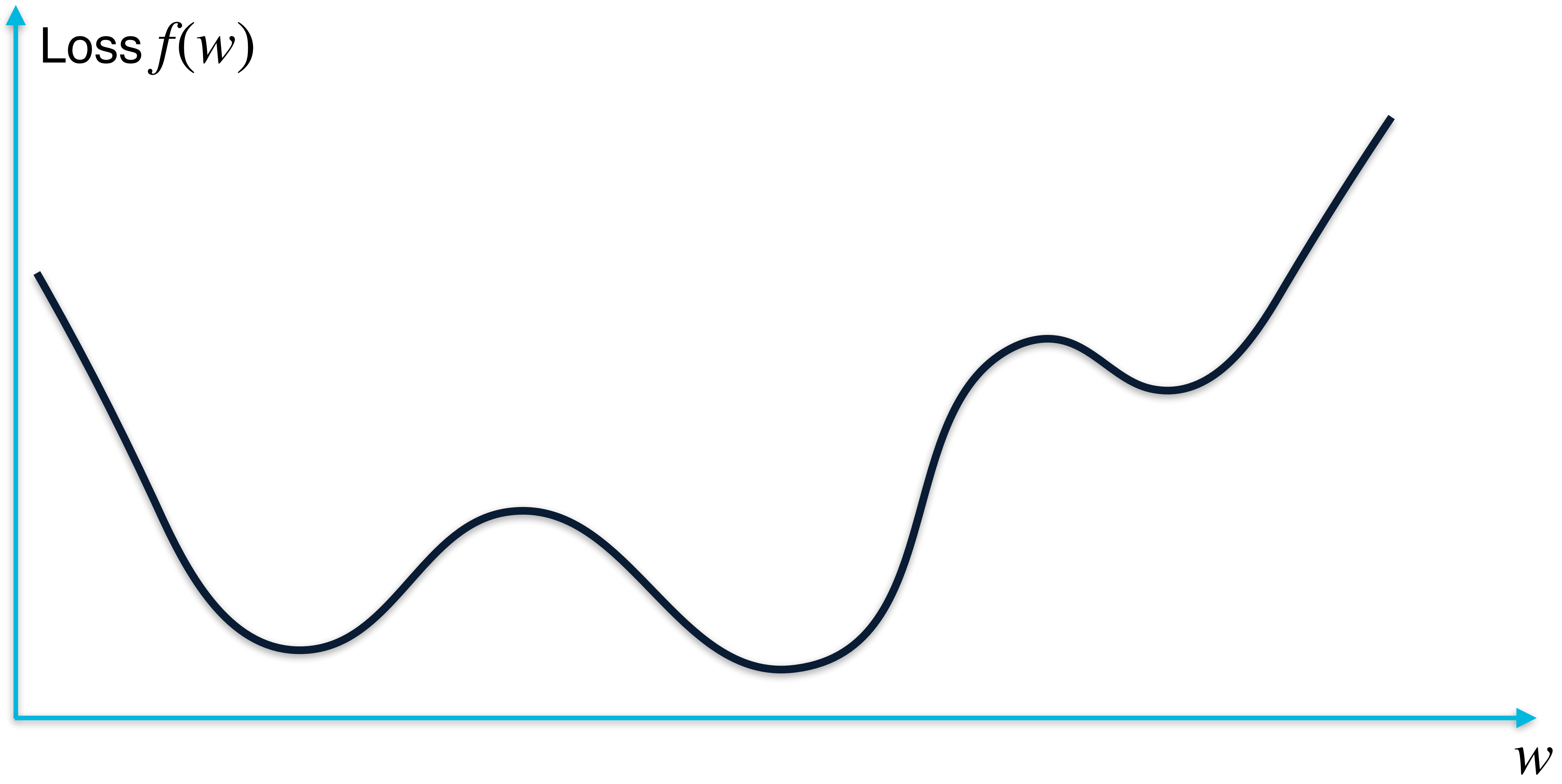



Loss $f(w)$
w

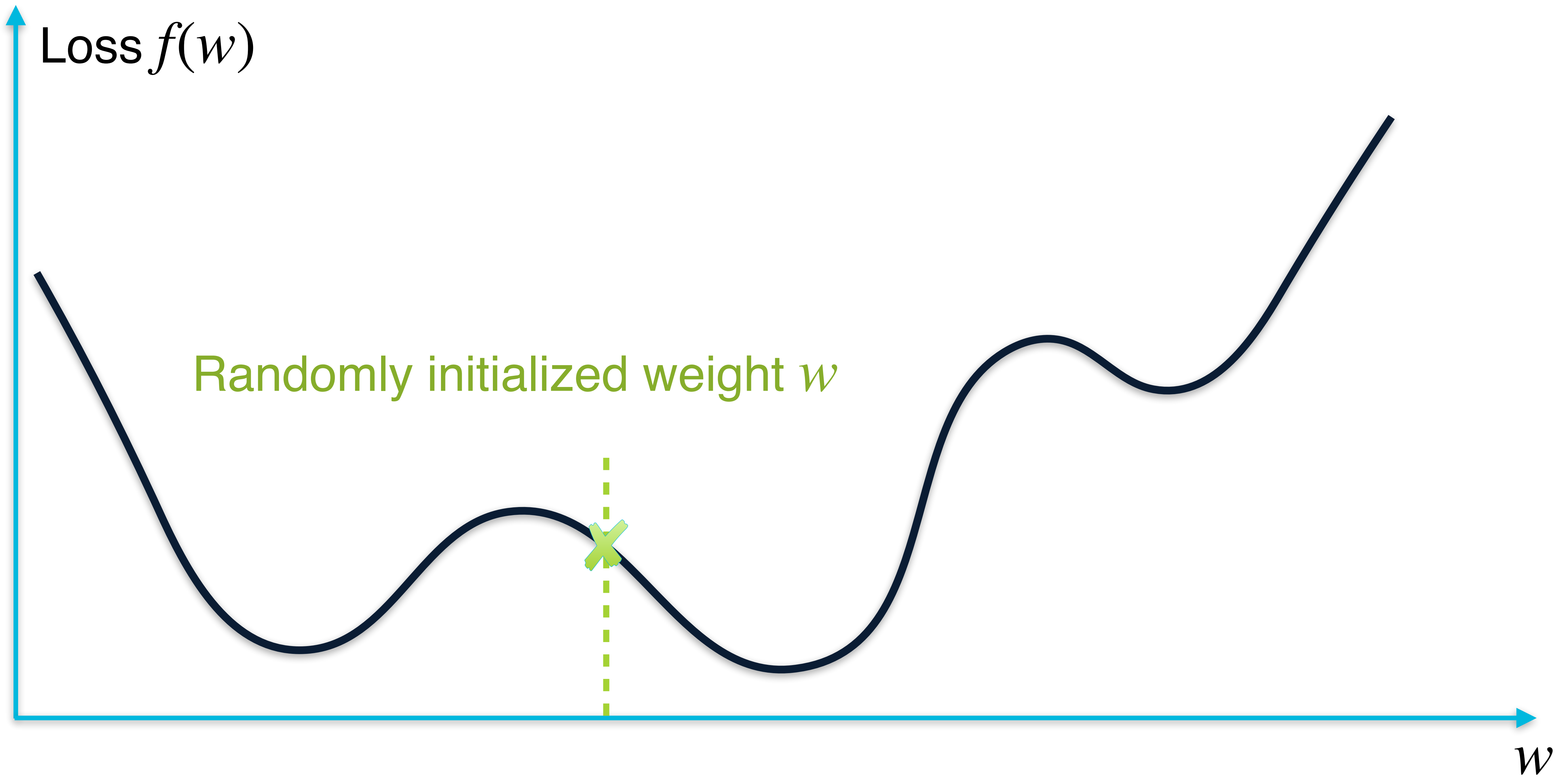
- **Solution: Gradient descent**



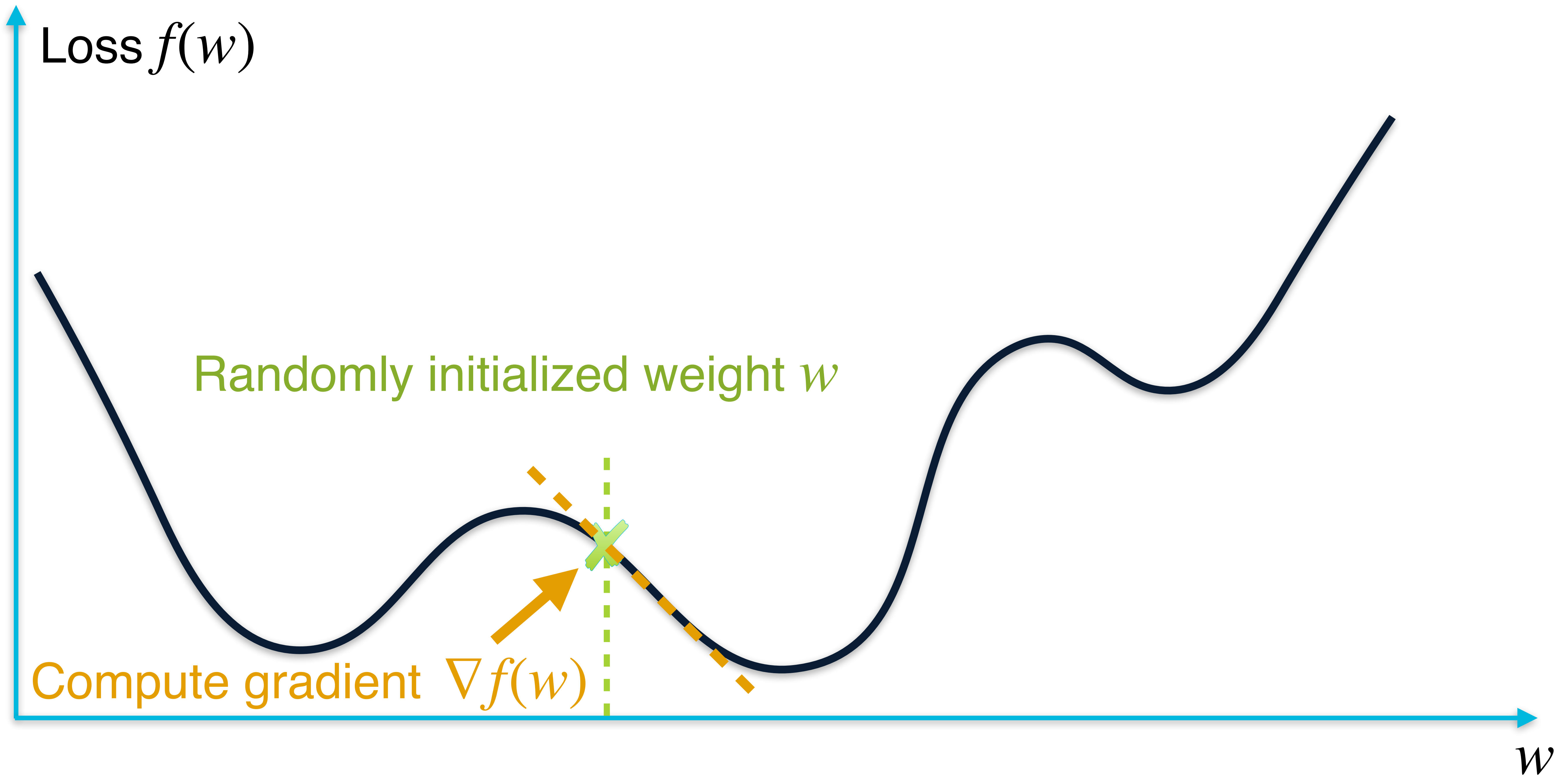
- **Solution: Gradient descent**



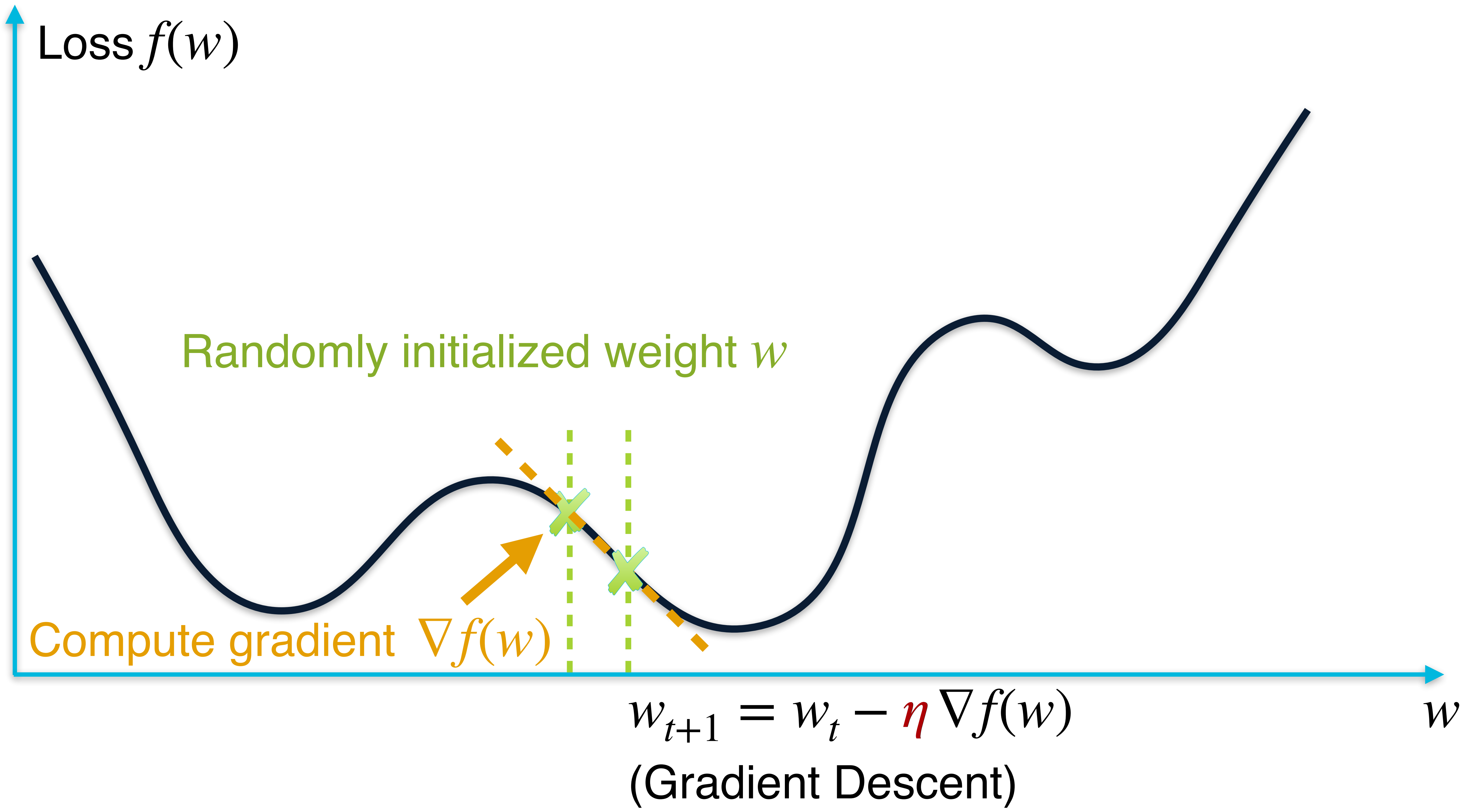
Solution: Gradient descent



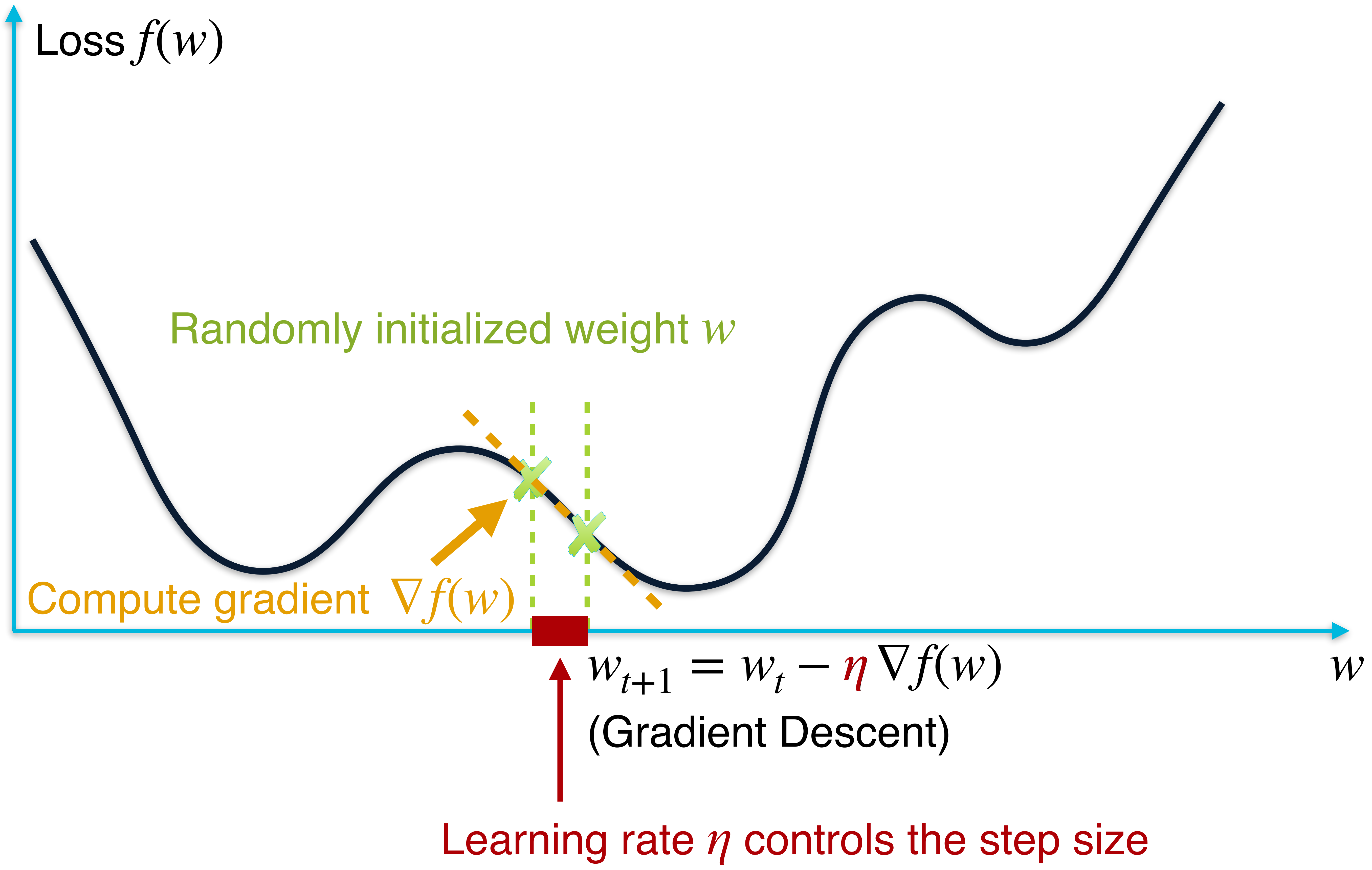
Solution: Gradient descent



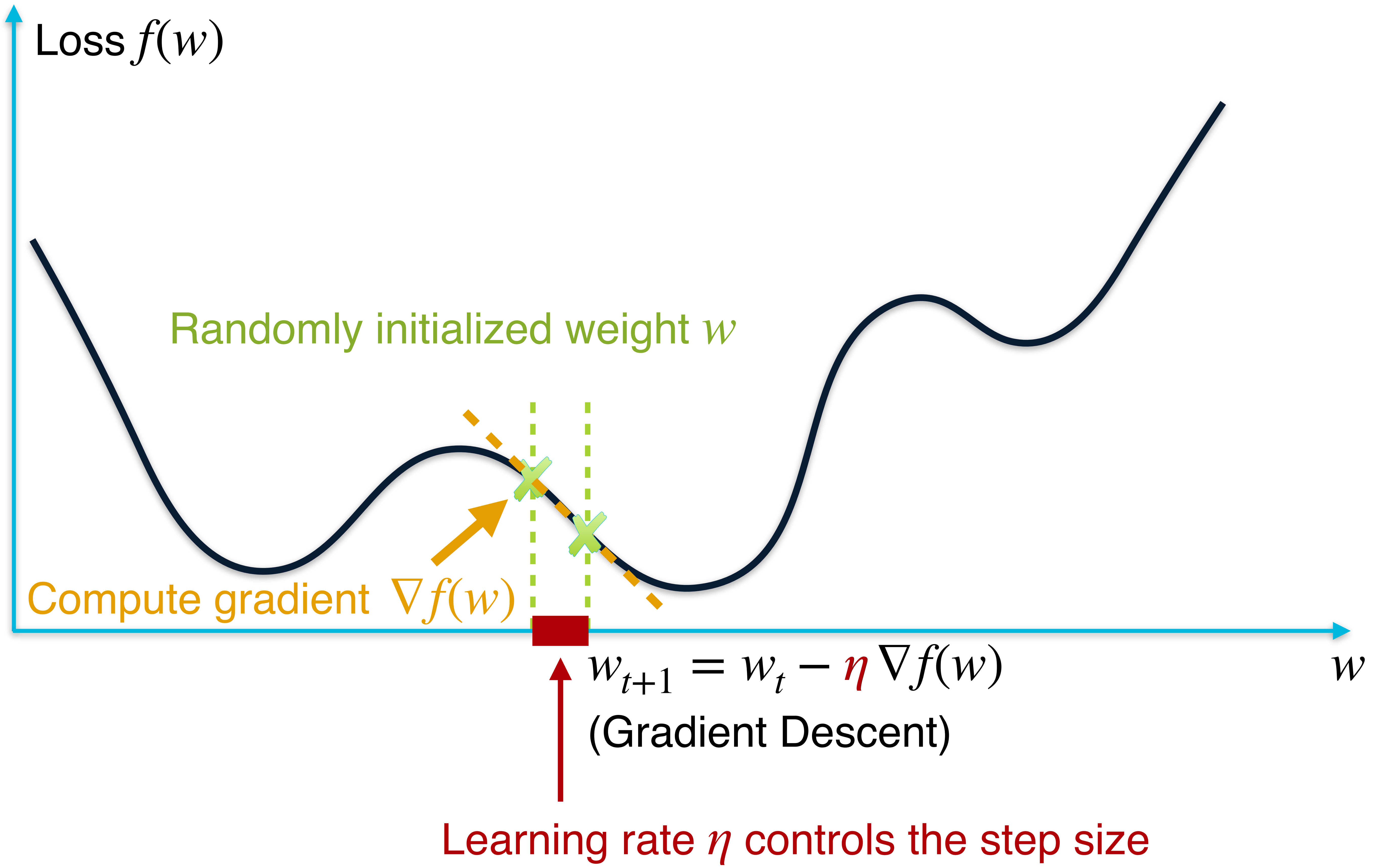
- **Solution: Gradient descent**



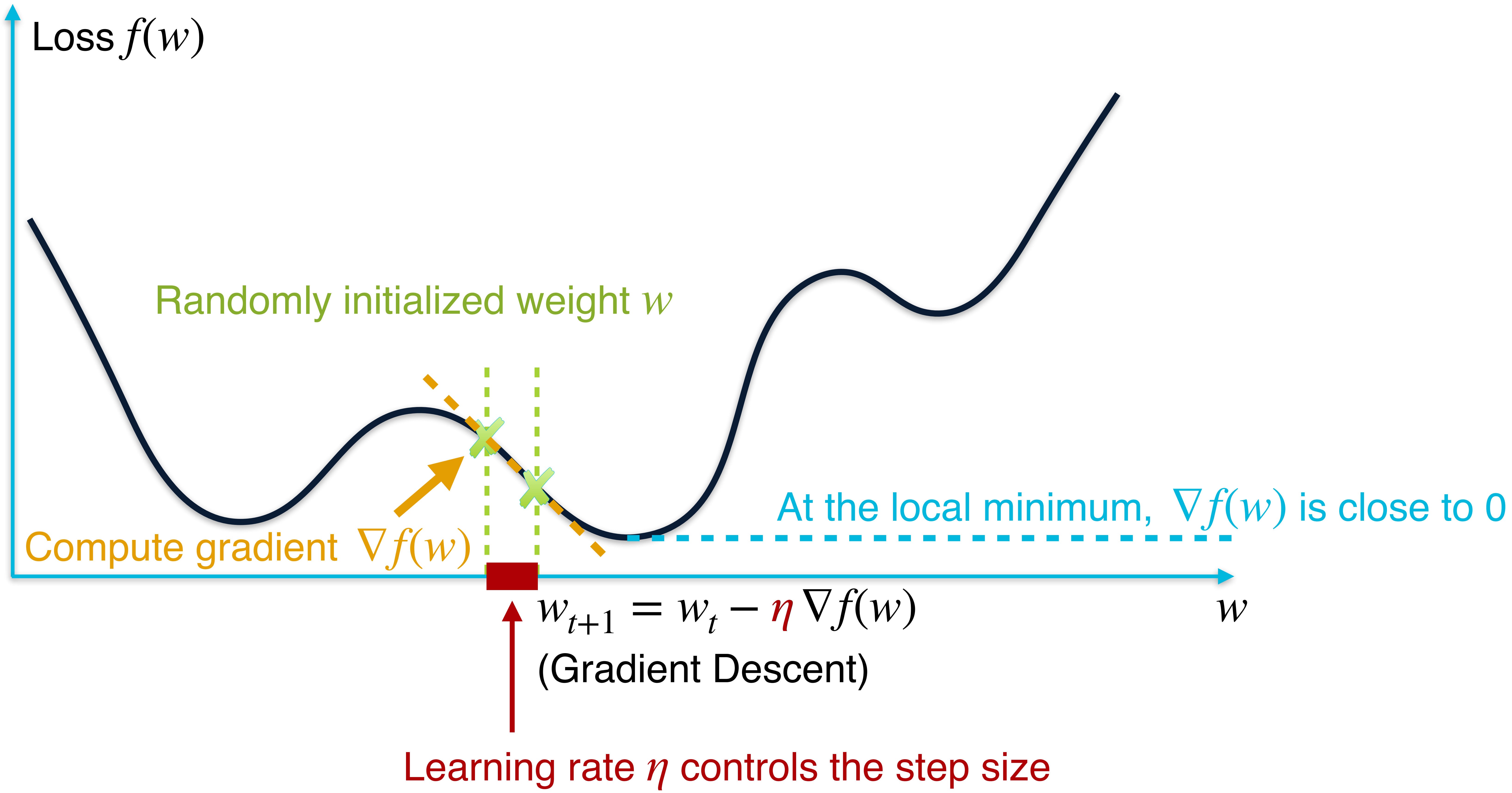
- **Solution: Gradient descent**



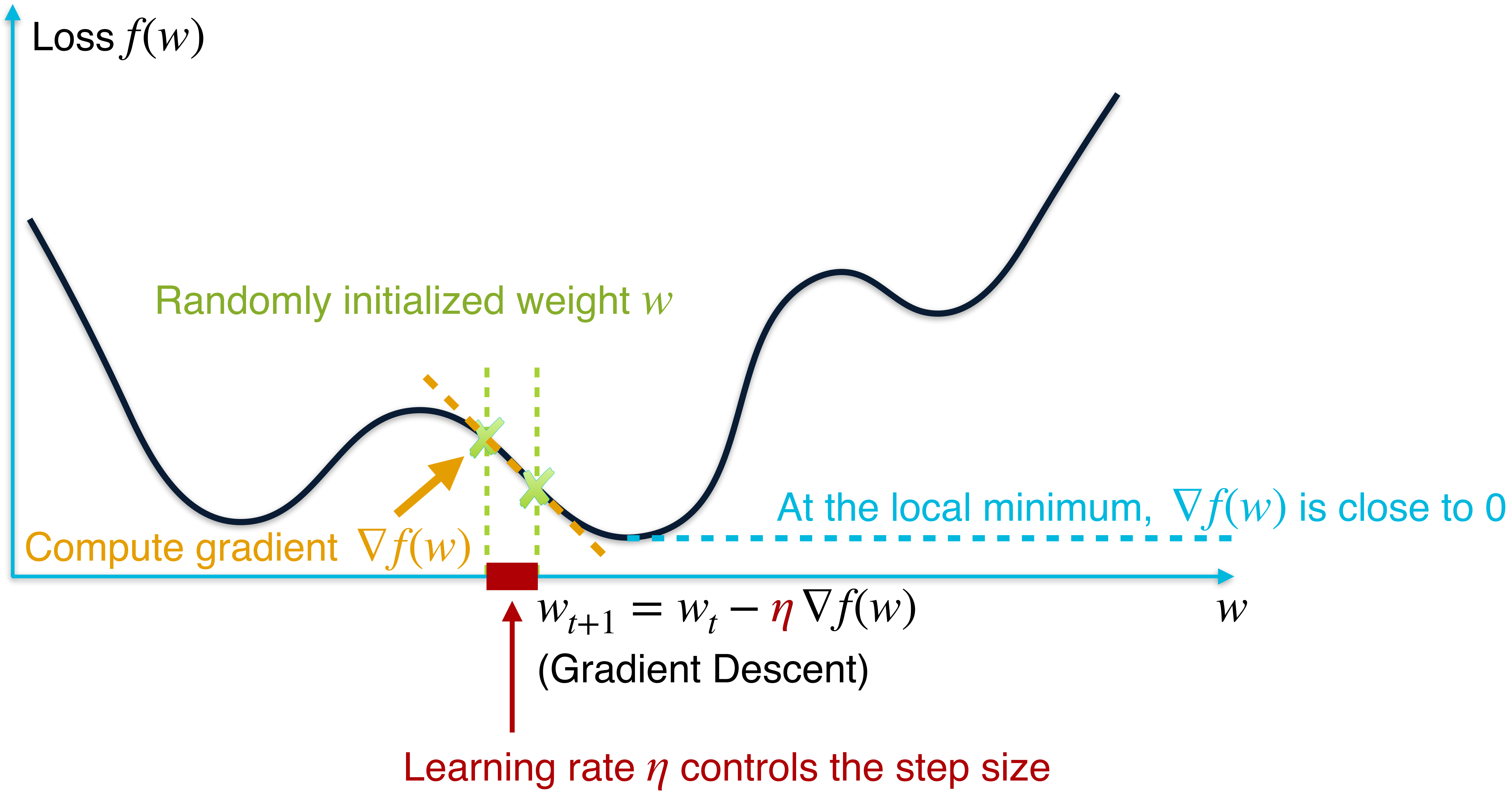
- **Solution: Gradient descent**
- **How to stop?**
  - When update is small enough
  - $||w_{t+1} - w_t|| \leq \varepsilon$ i.e., $||\nabla f(w_t)|| \leq \varepsilon$



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



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

- **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

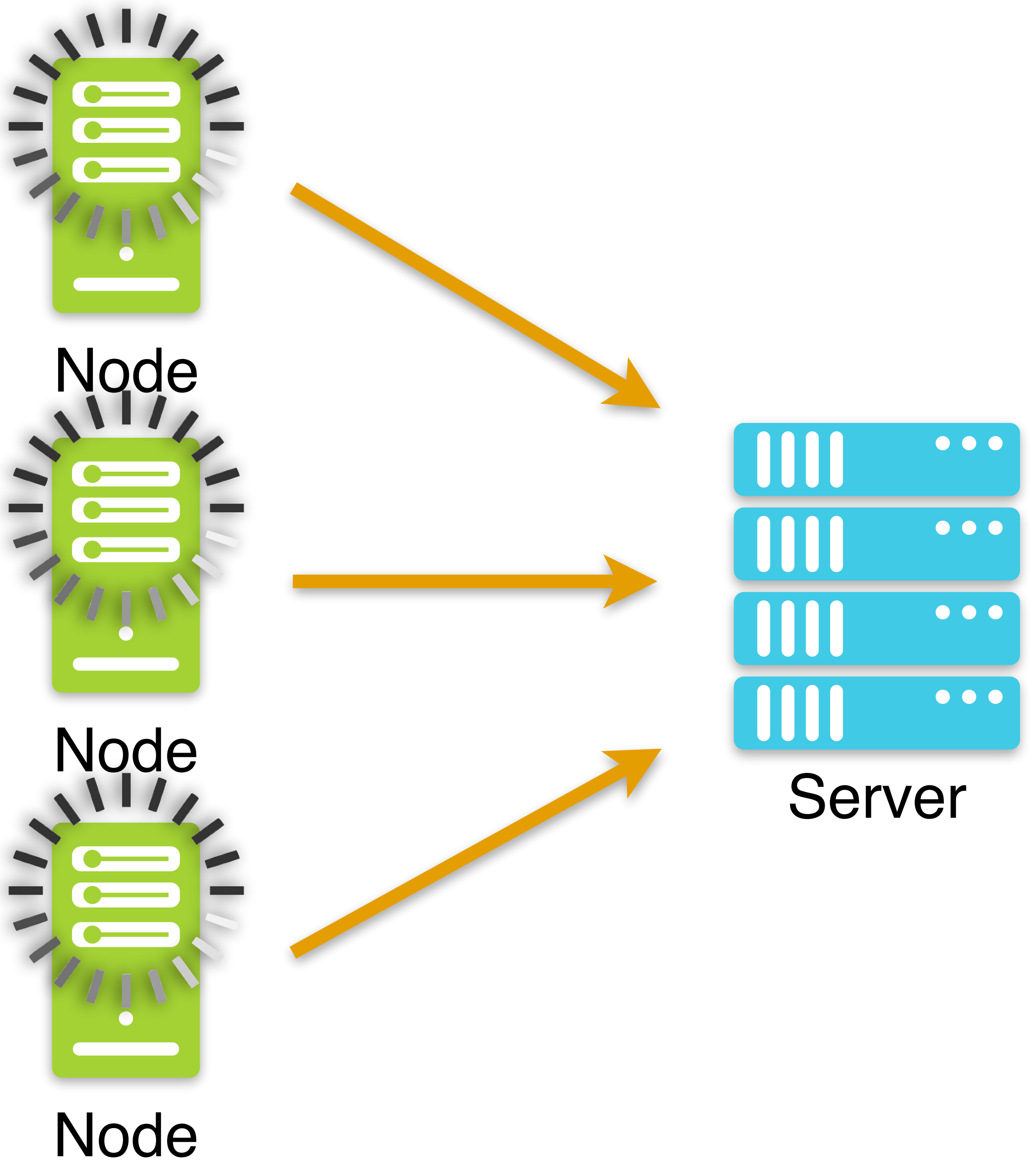
FEDERATED LEARNING CHALLENGES AND FEATURES

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

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

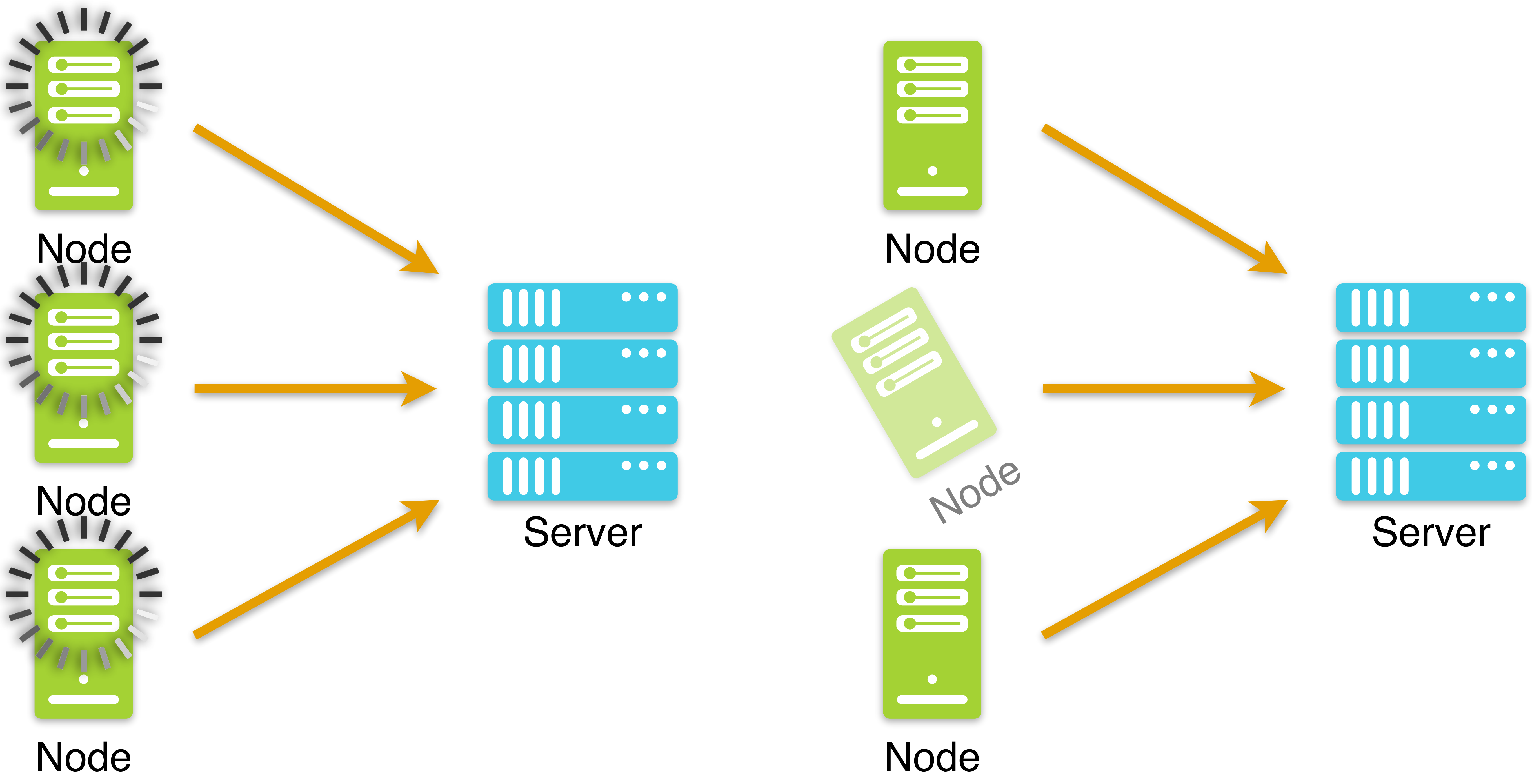
- **System issues**

System issues



Power consumption

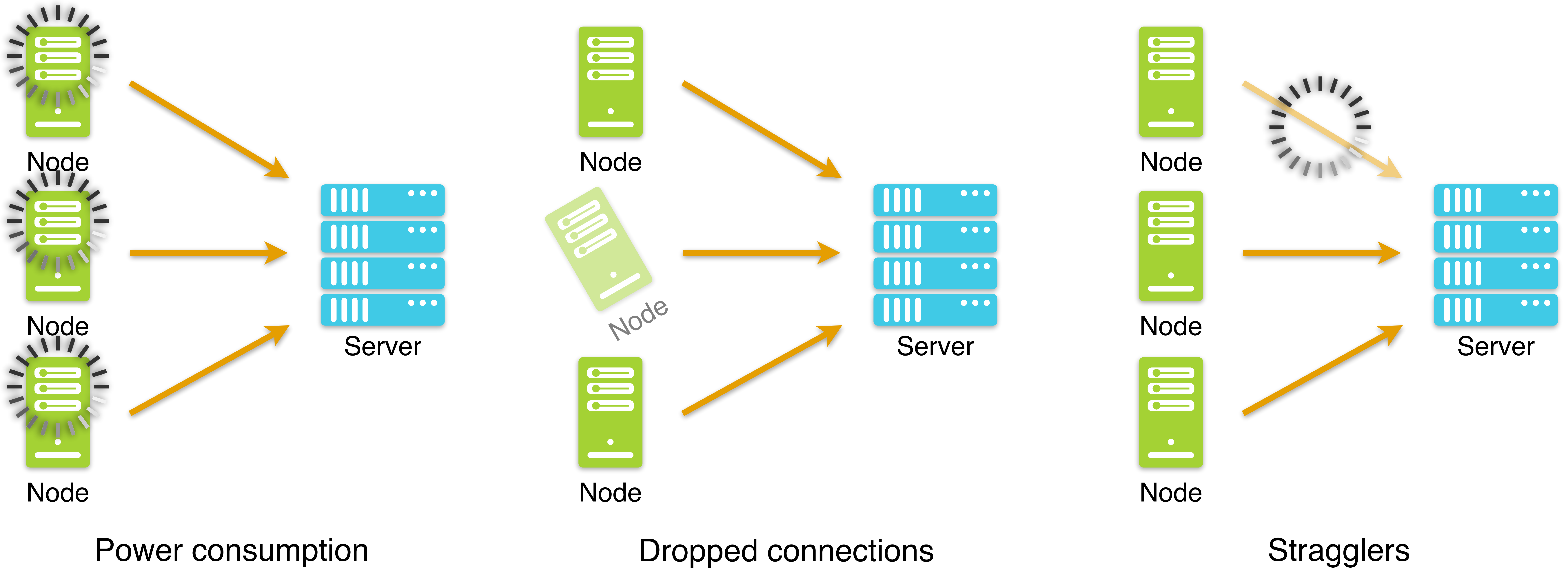
System issues



Power consumption

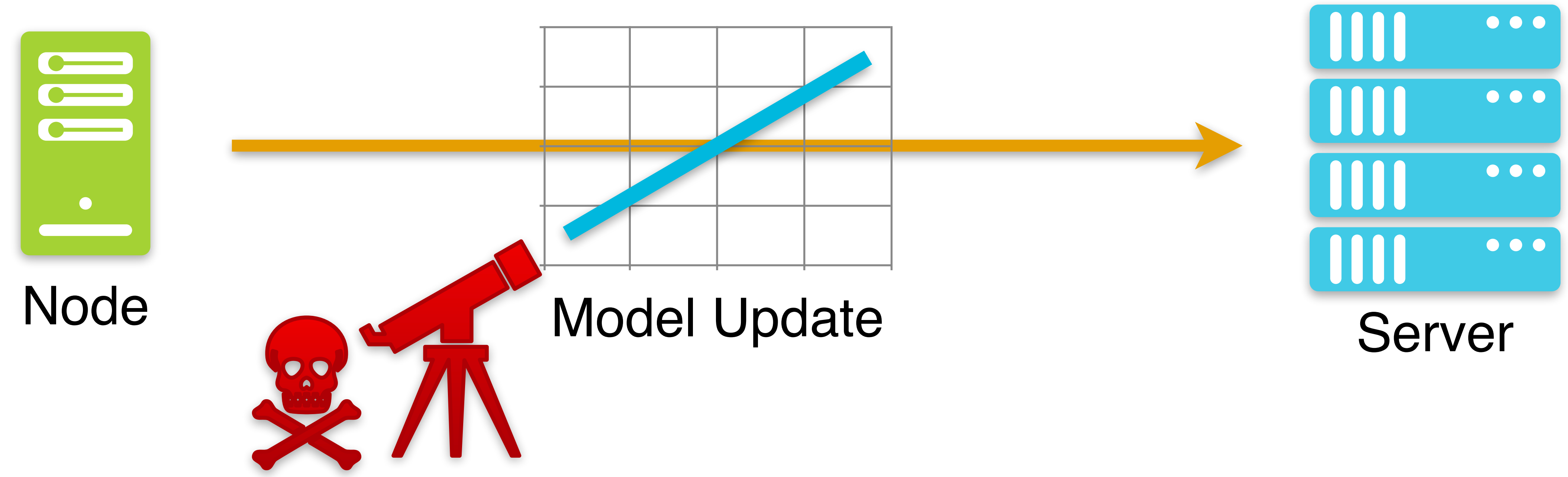
Dropped connections

System issues

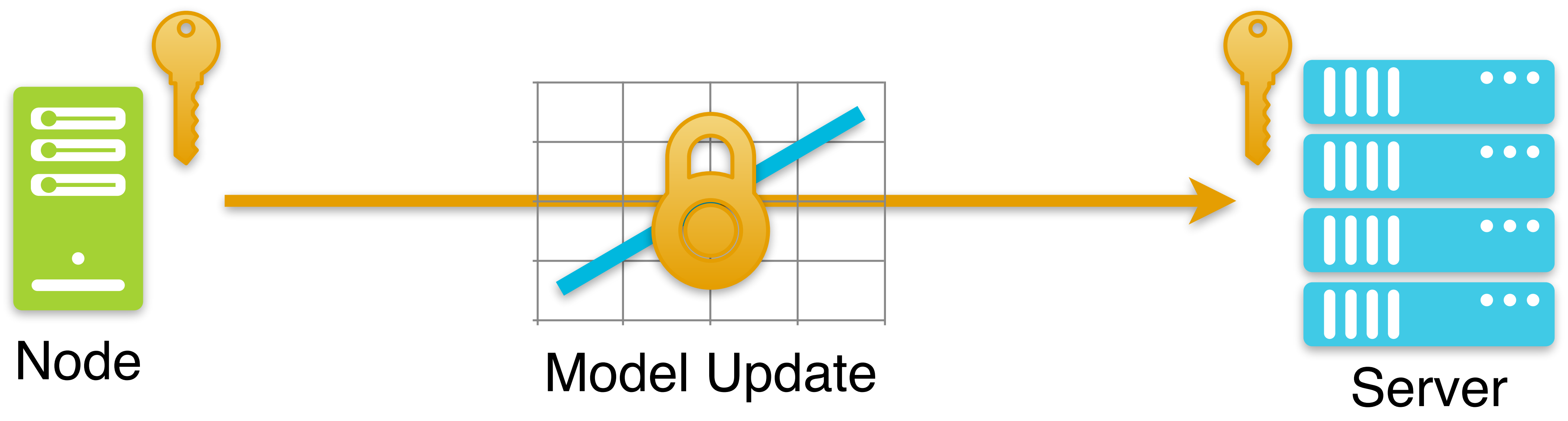


- **Privacy issues**

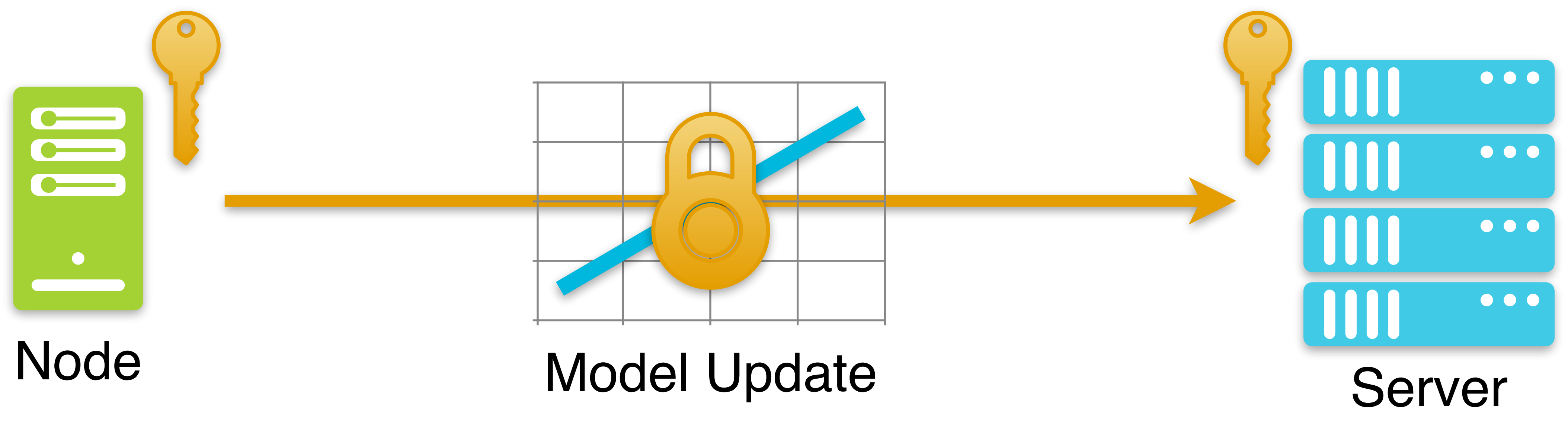
- **Privacy issues**
  - Man in the middle

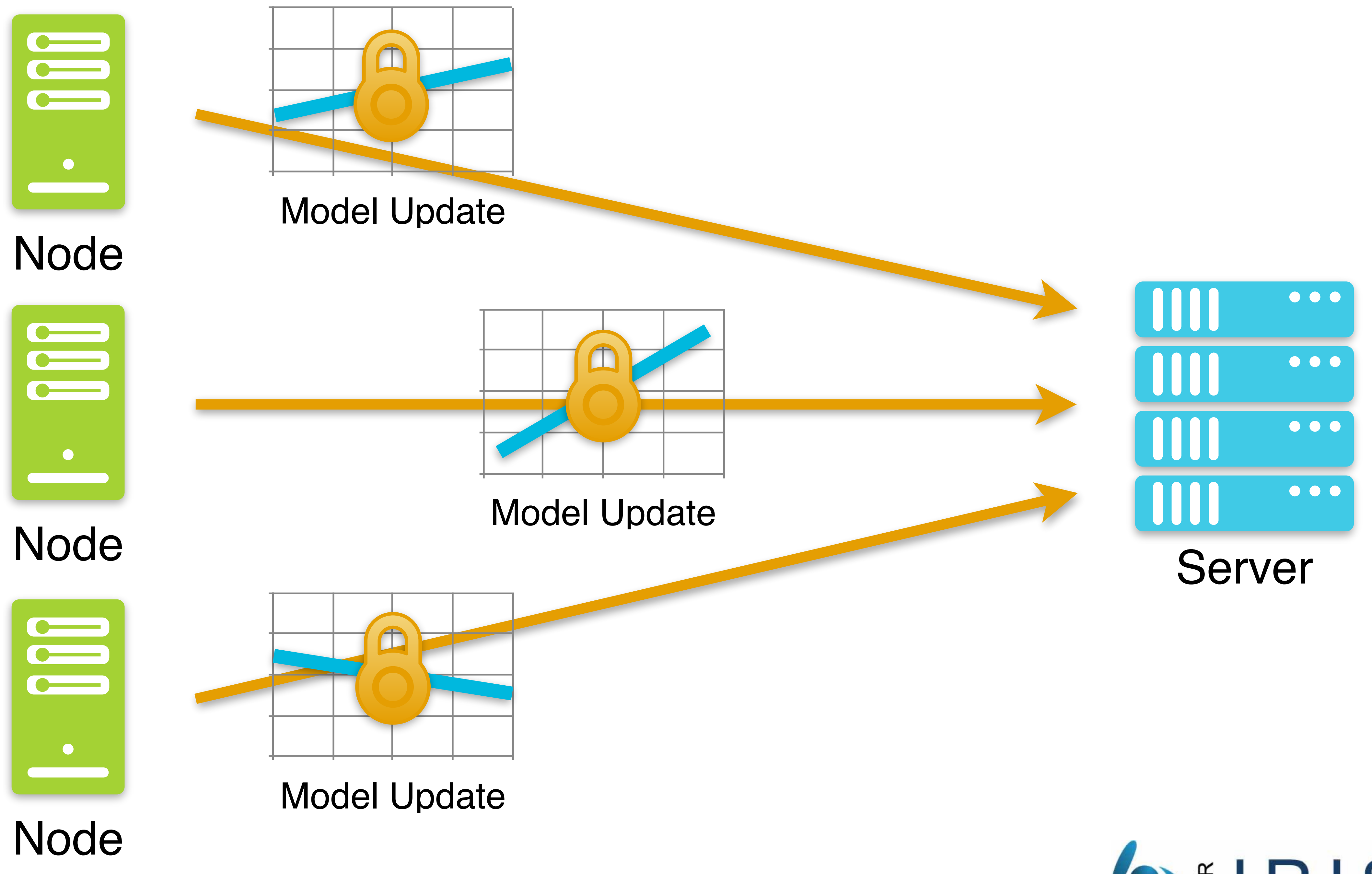


- **Privacy issues**
  - Man in the middle
    - End-to-end encryption

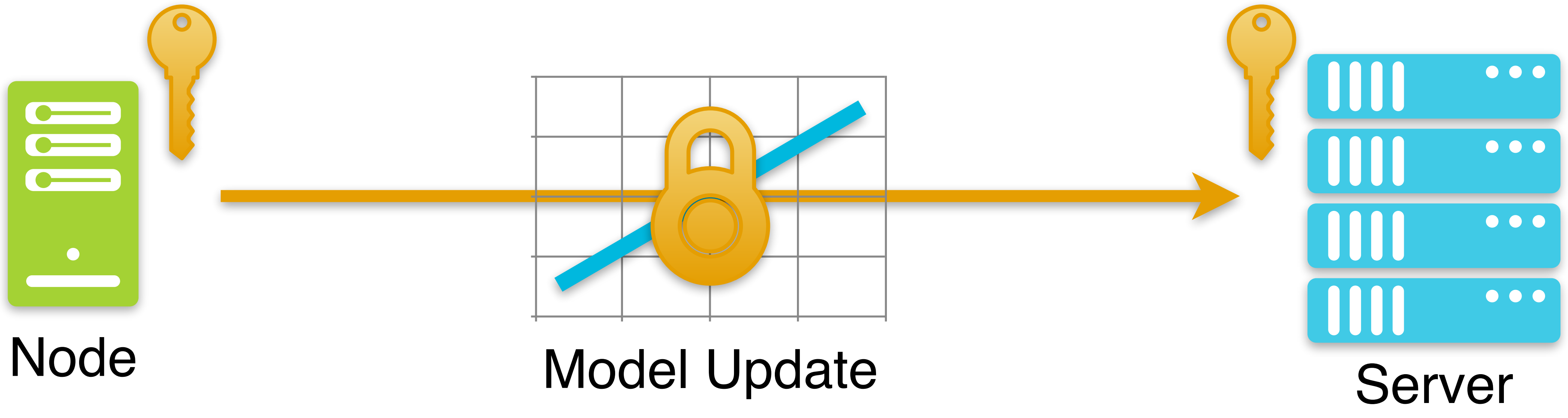


- **Privacy issues**
  - Man in the middle
    - End-to-end encryption
  - Honest-but-curious server

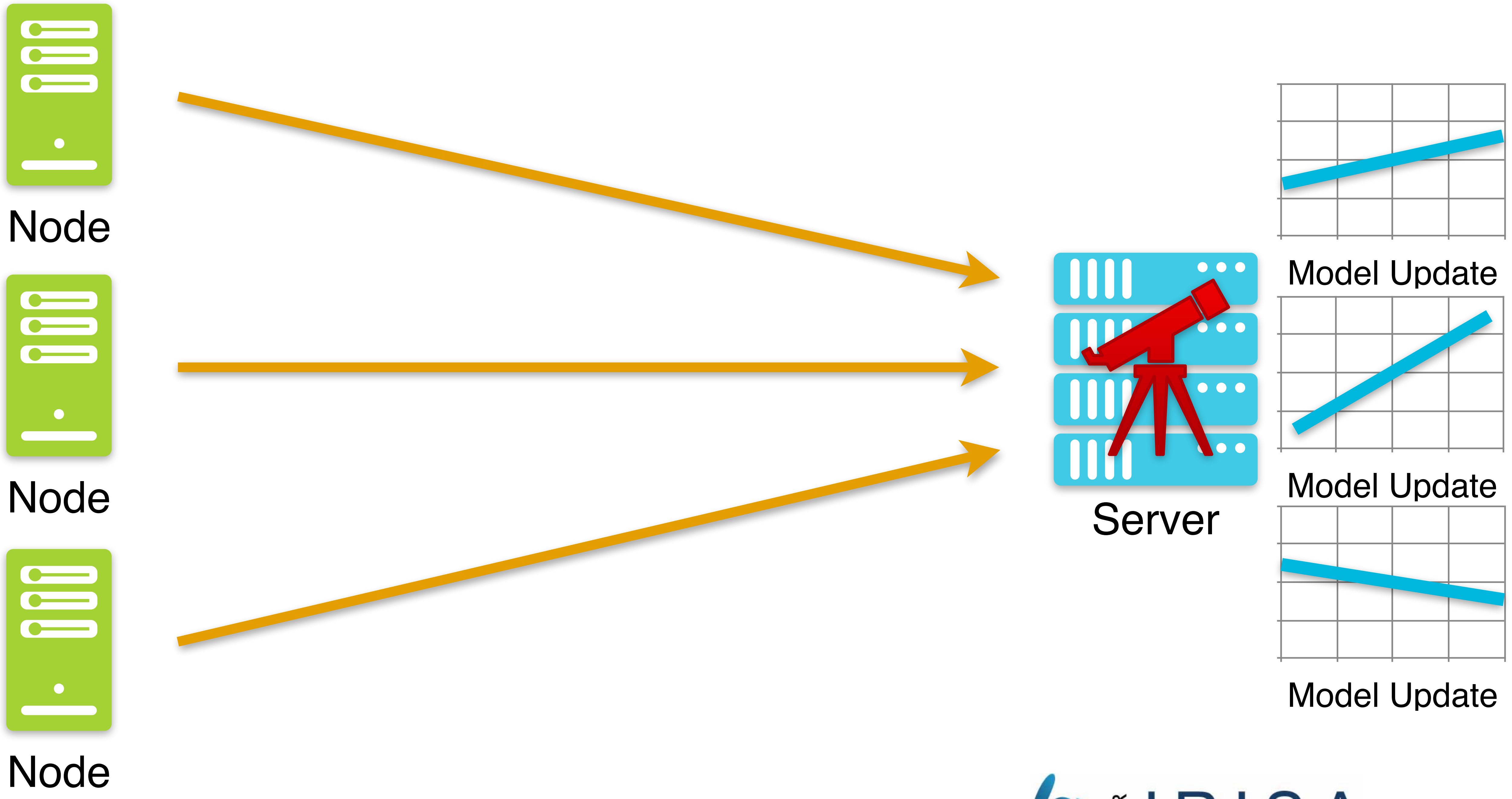




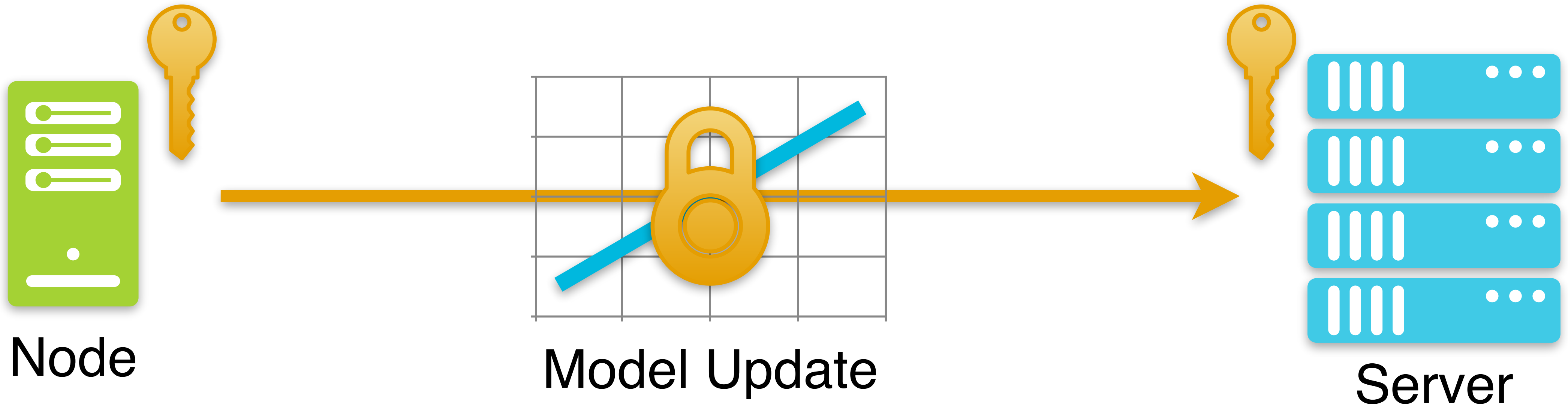
- **Privacy issues**
  - Man in the middle
    - End-to-end encryption



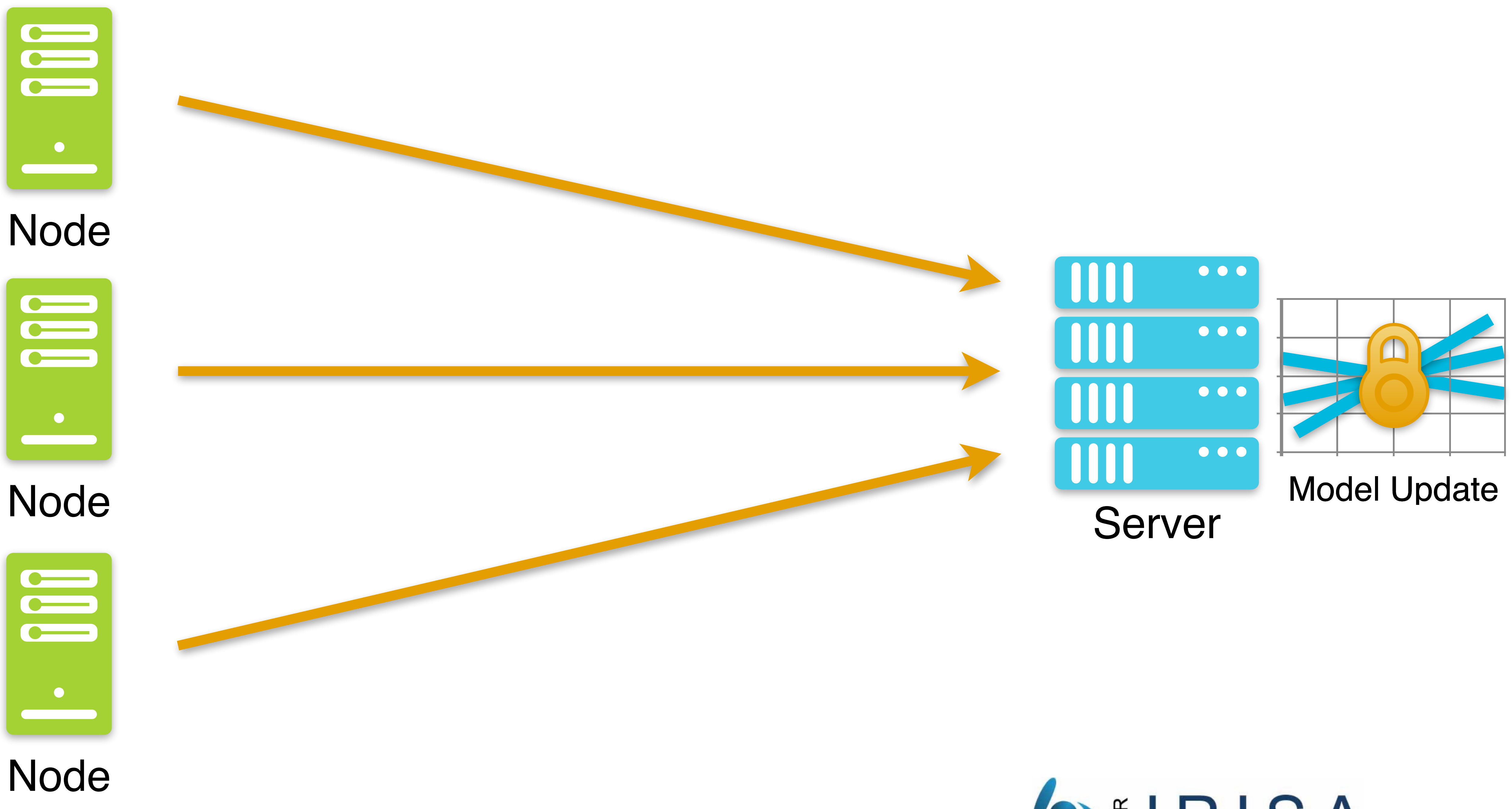
  - Honest-but-curious server



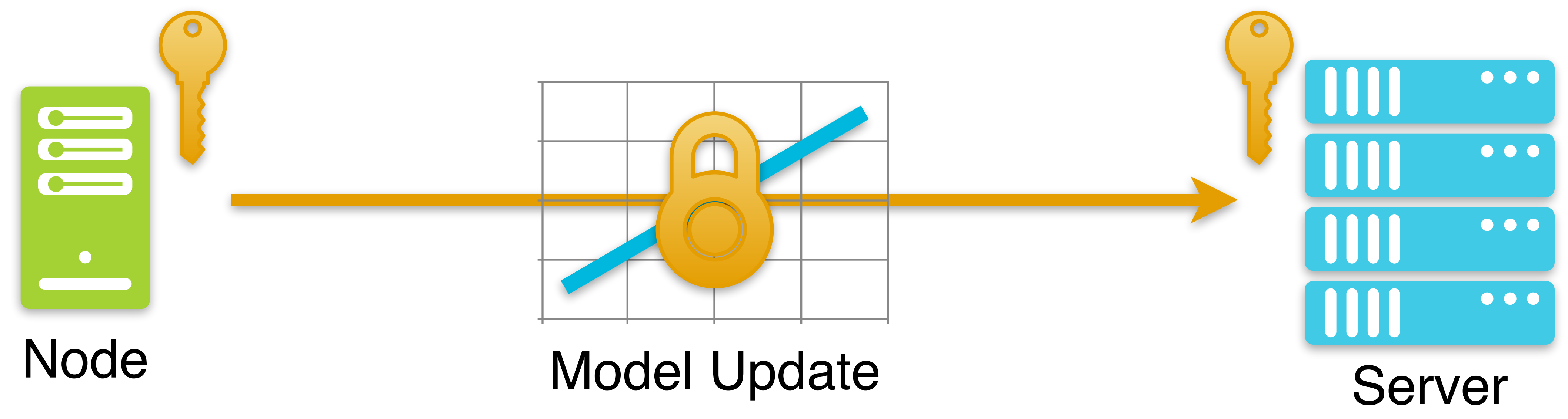
- **Privacy issues**
  - Man in the middle
    - End-to-end encryption



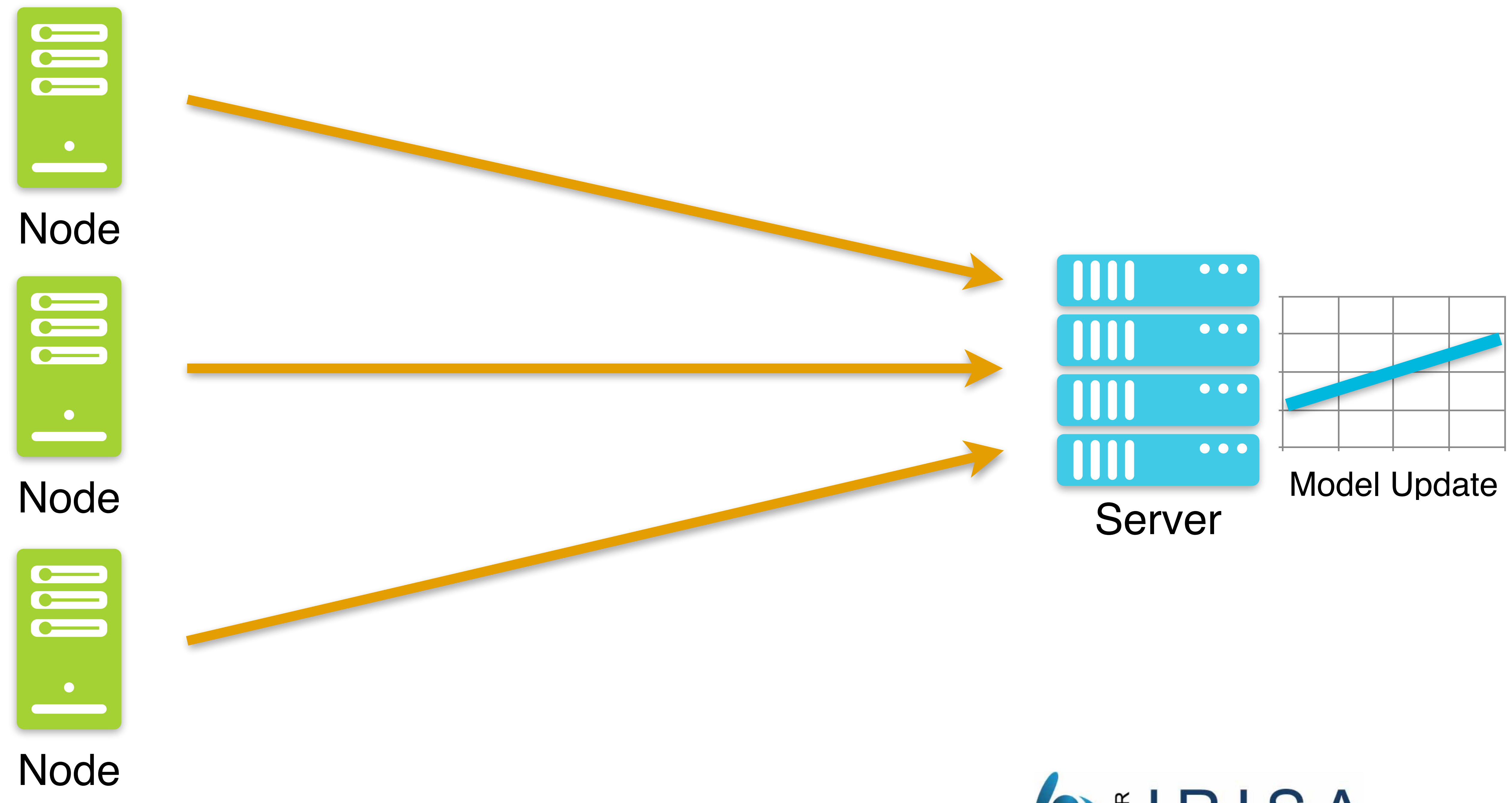
  - Honest-but-curious server
    - Secure aggregation



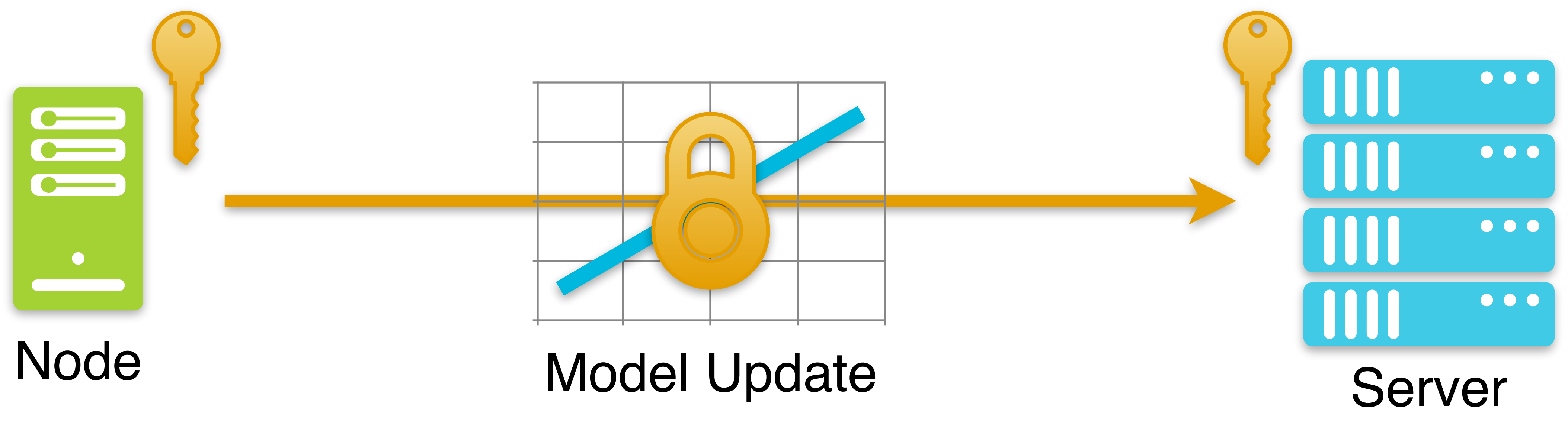
- **Privacy issues**
  - Man in the middle
    - End-to-end encryption



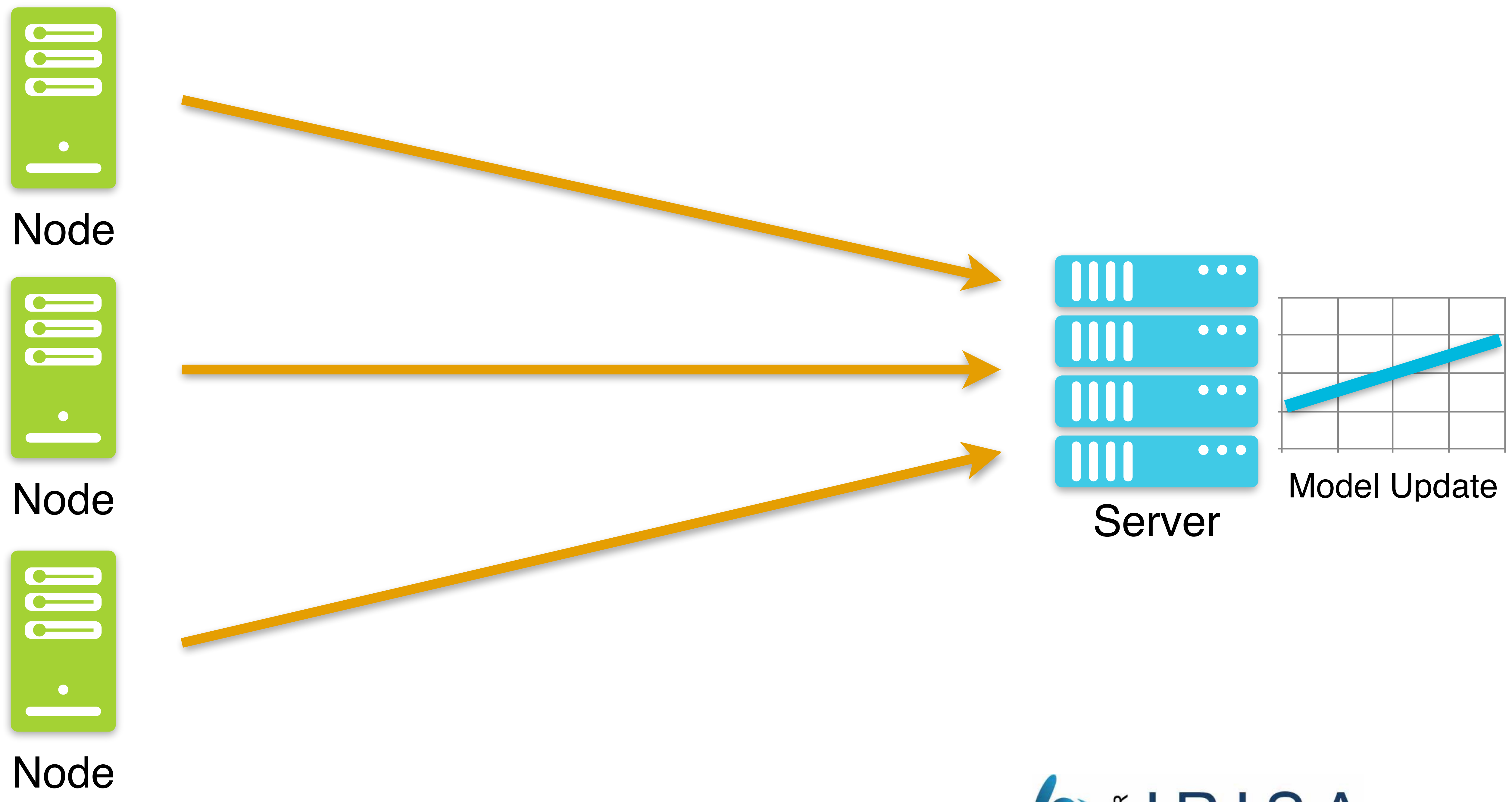
  - Honest-but-curious server
    - Secure aggregation

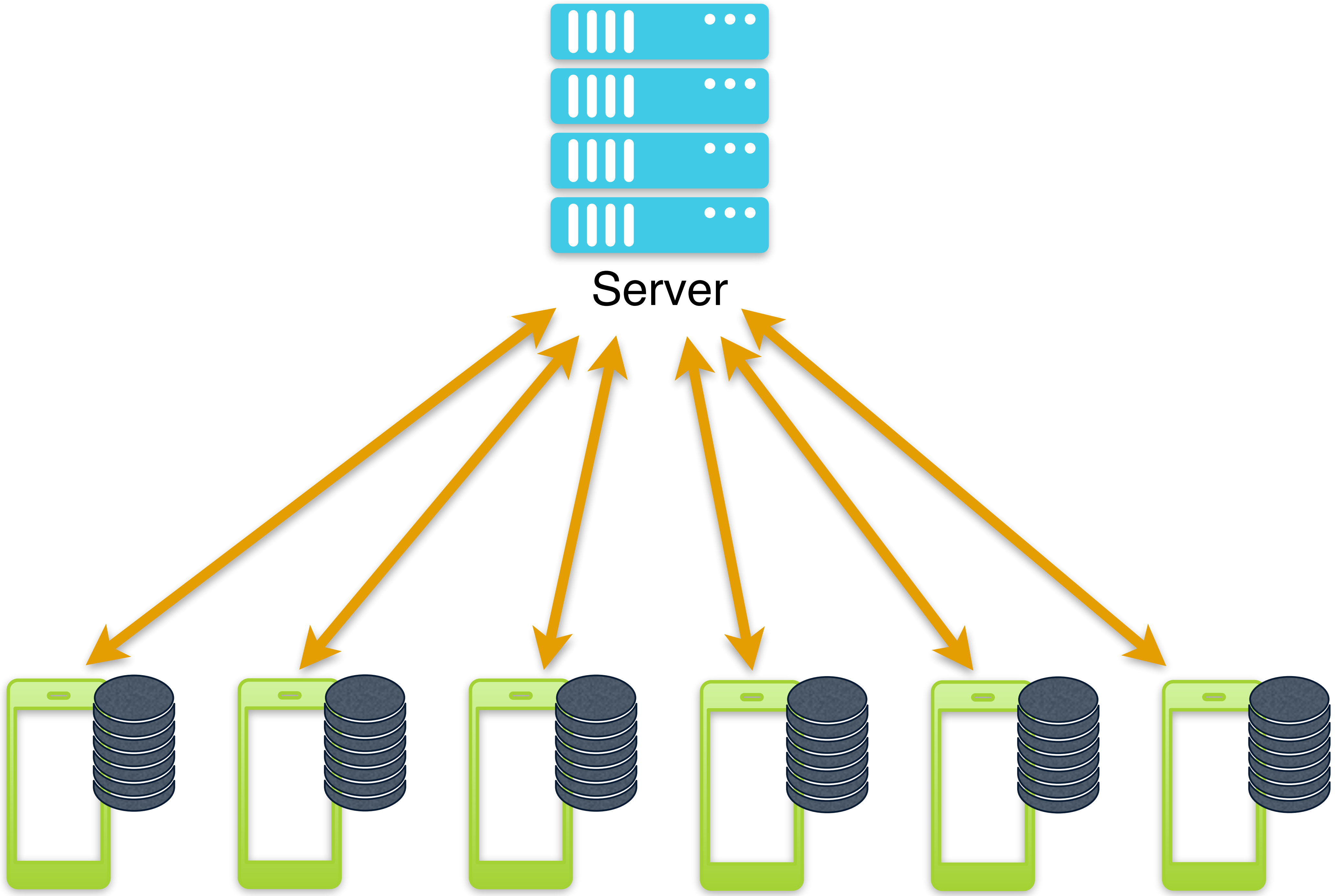


- **Privacy issues**
  - Man in the middle
    - End-to-end encryption



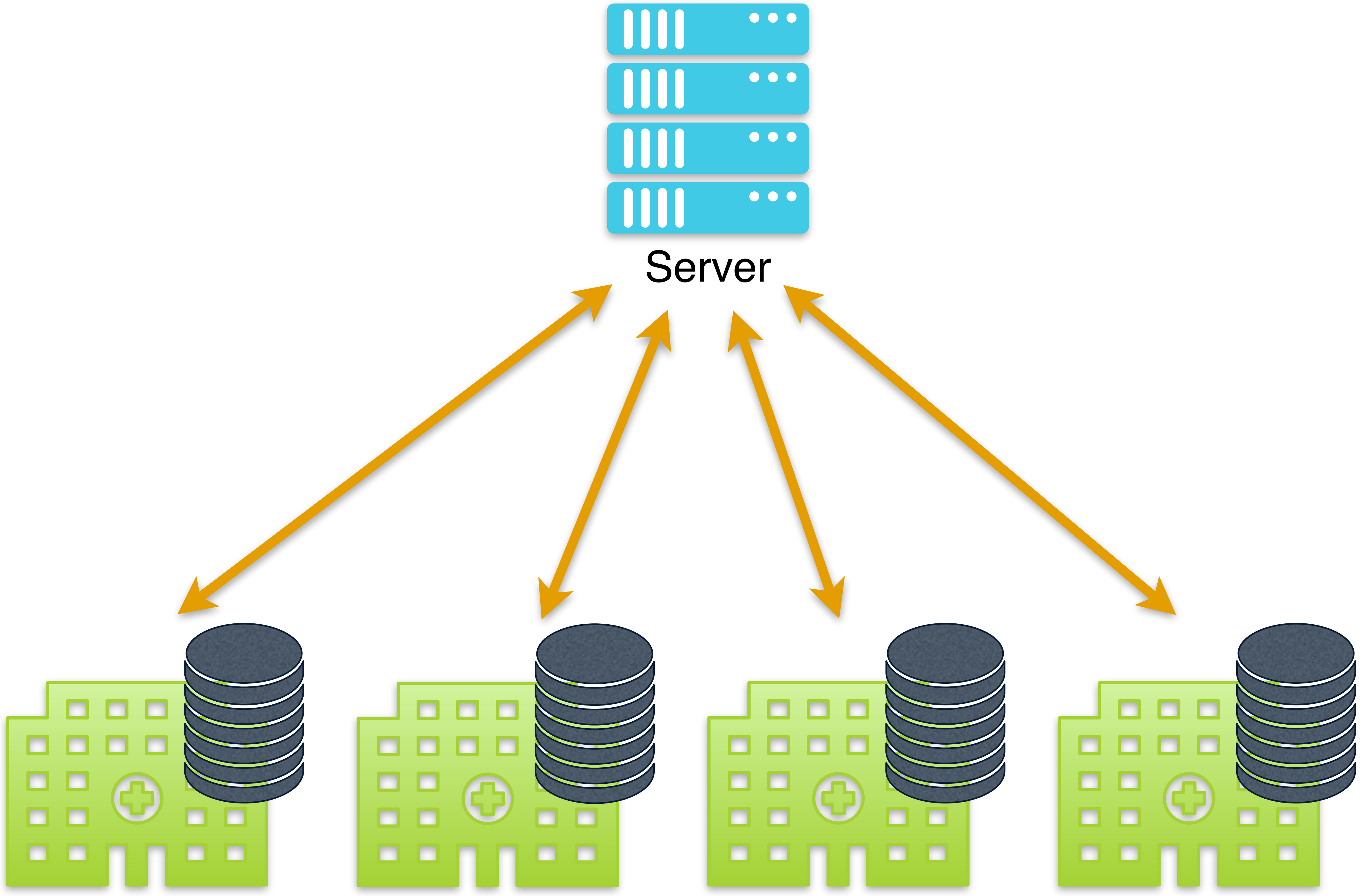
  - Honest-but-curious server
    - Secure aggregation
    - Differential Privacy for increased security





Cross-device FL

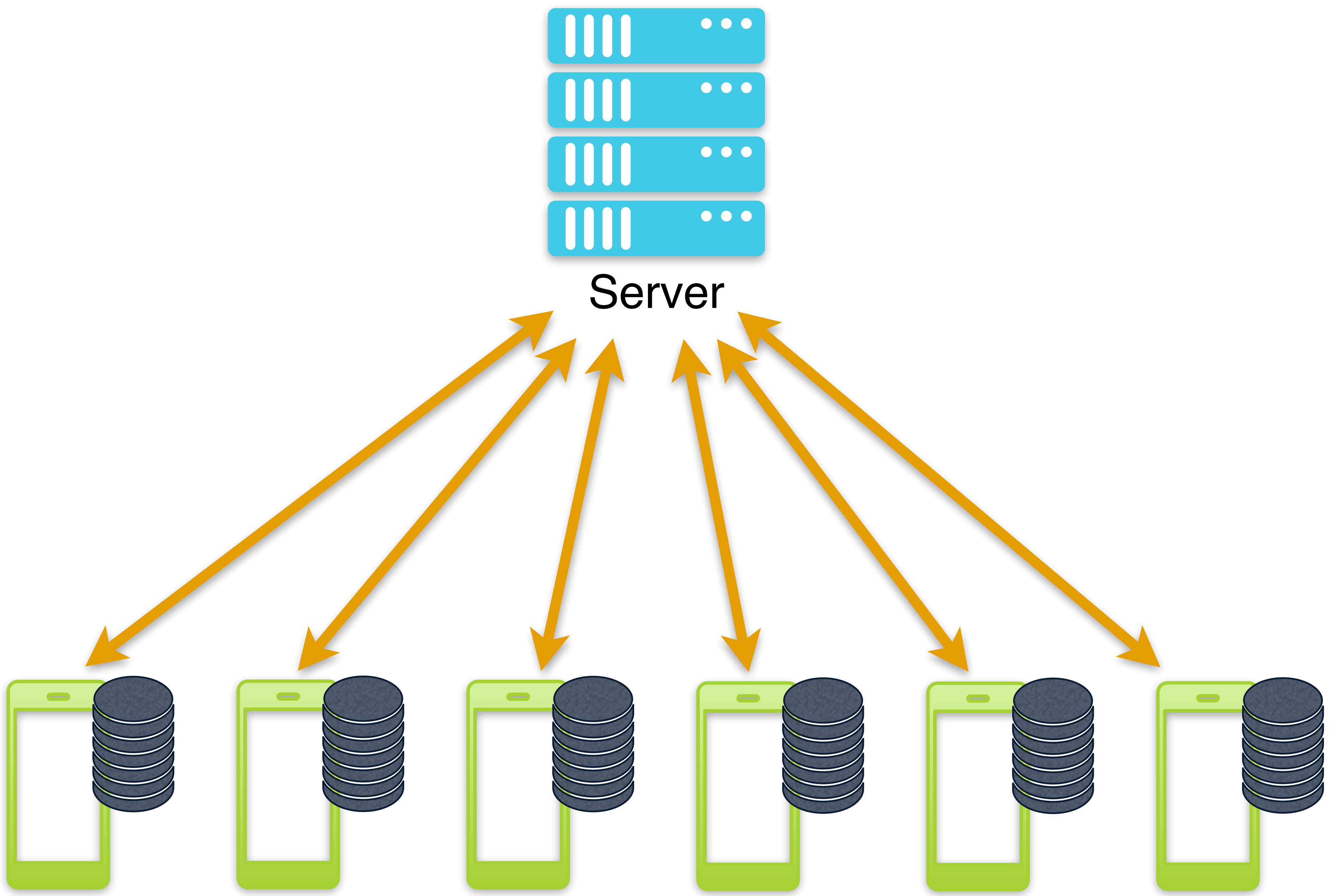
- **Massive number of parties**
  - up to 10^{10}
- **Small dataset per party**
  - could be size 1
- **Limited availability and reliability**
- **Some parties may be malicious**



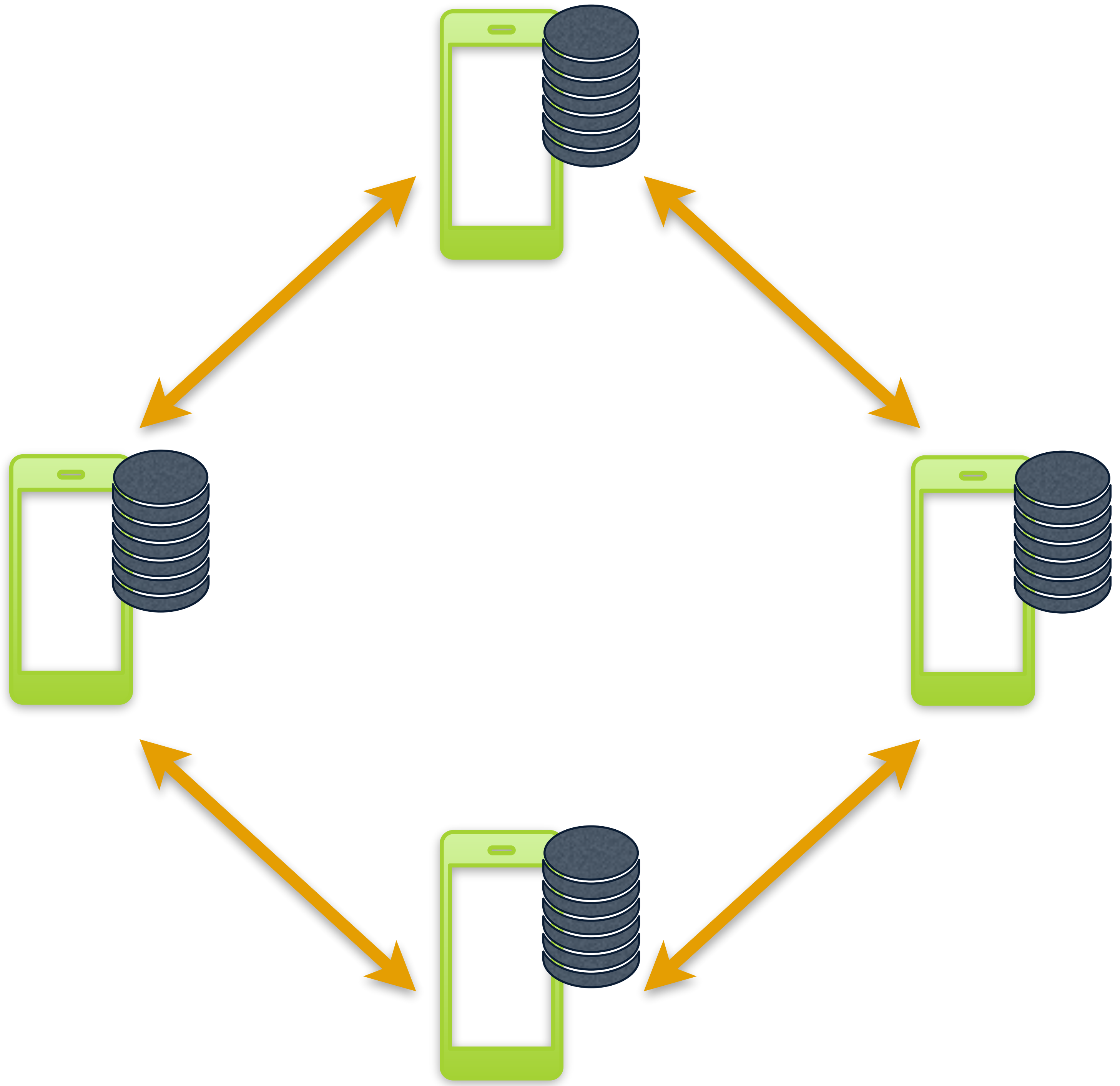
Cross-silo FL

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

SERVER ORCHESTRATED VS. FULLY DECENTRALIZED FL

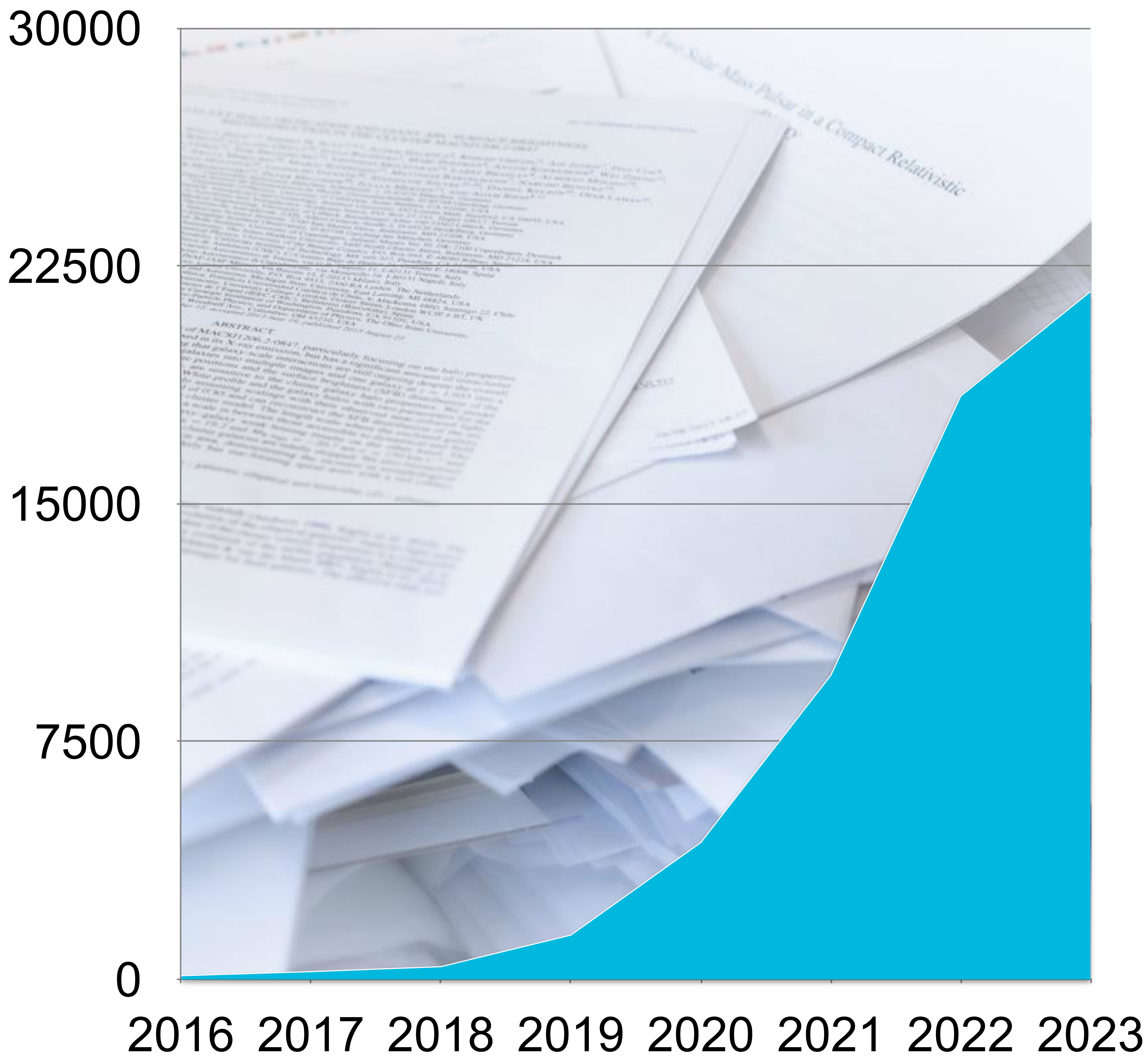


- Server-client communication
- Global coordination, global aggregation
- Server is a single point of failure and may become a bottleneck



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

- **Historical**
  - 2016: the term FL is first coined by Google researchers
  - 2018: « just » 180 papers on FL
  - 2022: more than 18k papers on FL! (*Google Scholar*)
- **Some real-world deployments by companies and researchers**
- **Several open-source libraries are under development:**
  - PySyft, TensorFlow Federated, FATE, Flower, 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

http://bit.ly/FLxSecu-part1

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

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

THE POWER OF FEDERATED LEARNING FOR NETWORK SECURITY

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

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

THE POWER OF FEDERATED LEARNING FOR NETWORK SECURITY

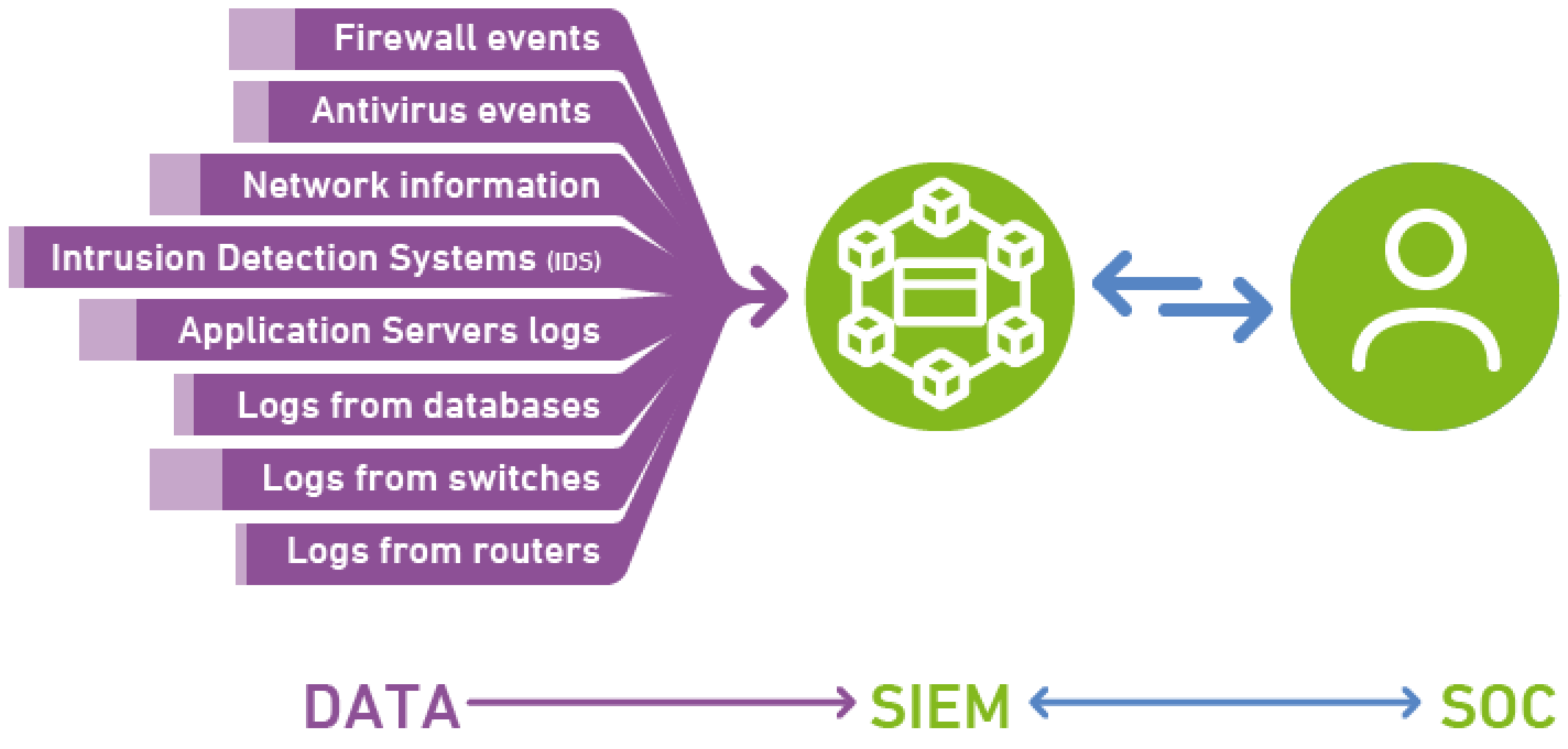
IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

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

- **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

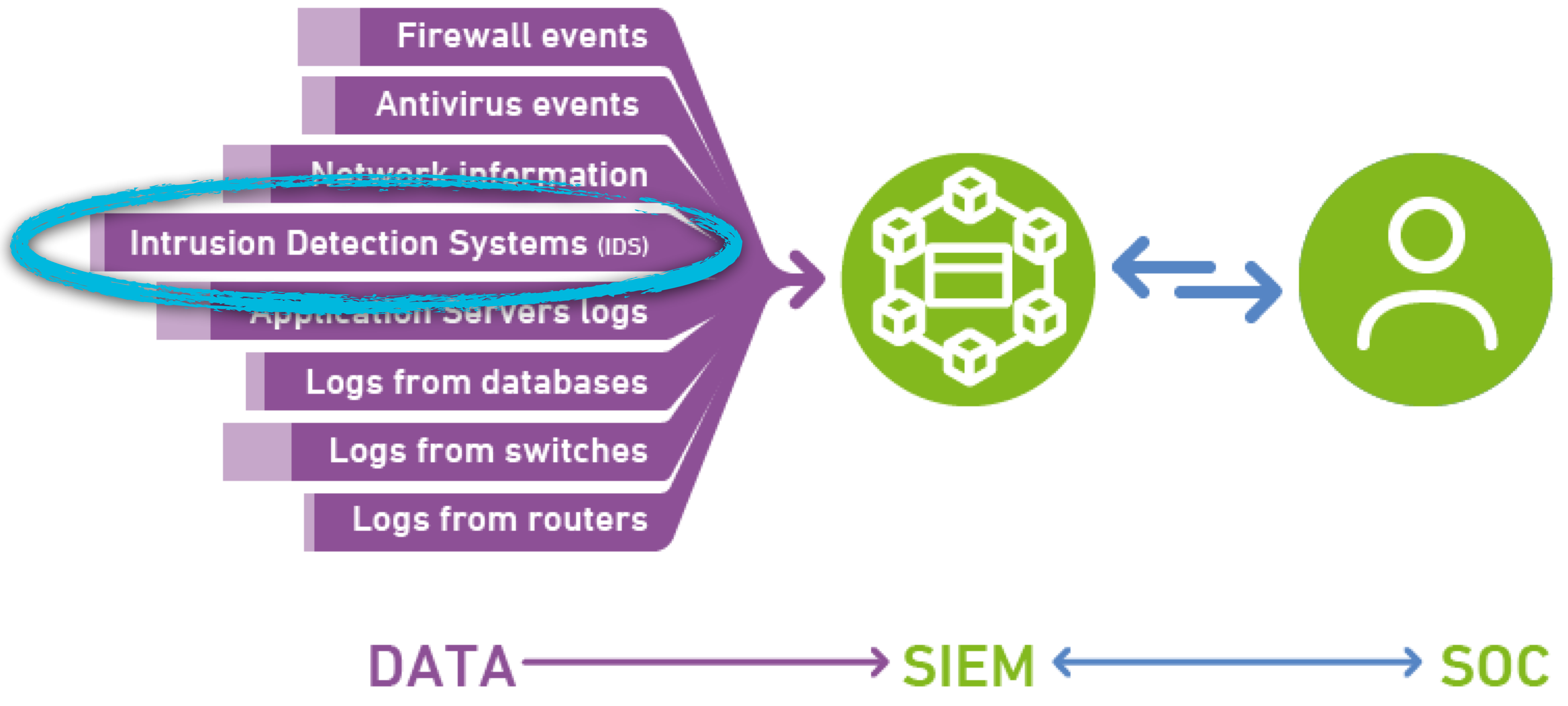


* SOC = Security Operation Center
* SIEM = Security Information and Event Management
* APT = Advanced Persistent Threat
* DDoS = Distributed Denial of Service

- **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



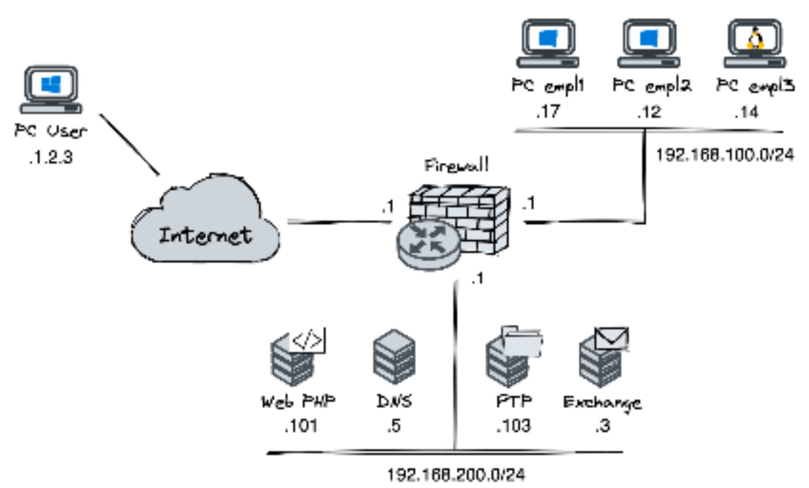
* SOC = Security Operation Center
* SIEM = Security Information and Event Management
* APT = Advanced Persistent Threat
* DDoS = Distributed Denial of Service

USE-CASE: INTRUSION DETECTION

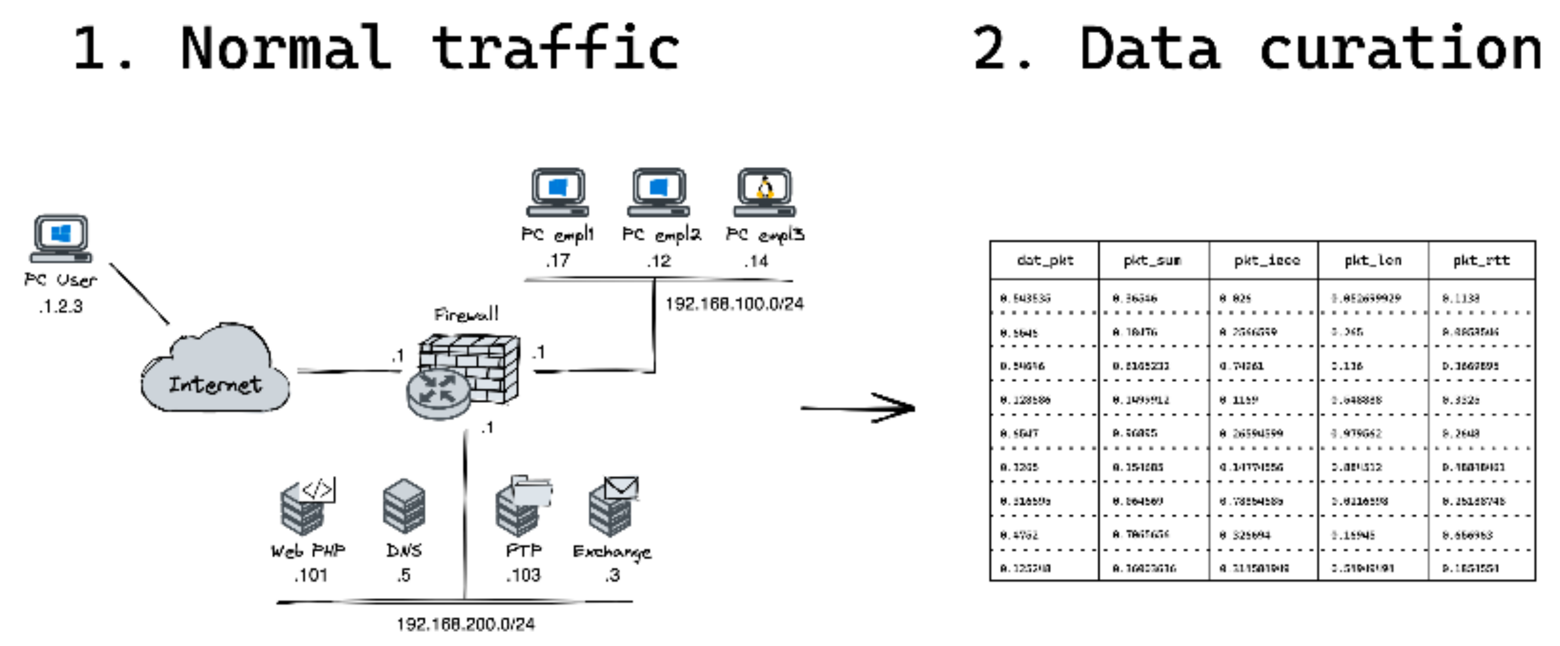
- **Different families:**
  - misuse detection, anomaly detection, specification-based…
- **Machine learning (ML) and deep learning (DL) often used for their performance**
  - *e.g.*, auto-encoder (AE) can be used for anomaly detection.
- **DL need a lot of data to be efficient, training them locally is a challenge**
  - *e.g.*, for AE, anything not known is an anomaly → higher false-positive rate.

- **Different families:**
  - misuse detection, anomaly detection, specification-based…
- **Machine learning (ML) and deep learning (DL) often used for their performance**
  - *e.g.*, auto-encoder (AE) can be used for anomaly detection.
- **DL need a lot of data to be efficient, training them locally is a challenge**
  - *e.g.*, for AE, anything not known is an anomaly → higher false-positive rate.

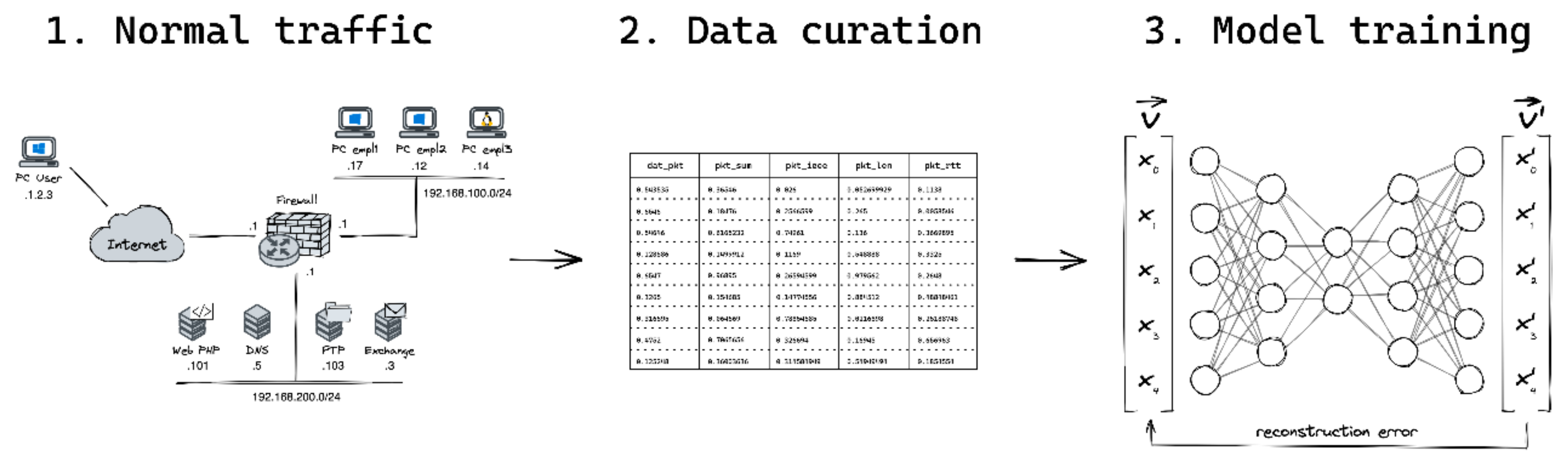
1. Normal traffic



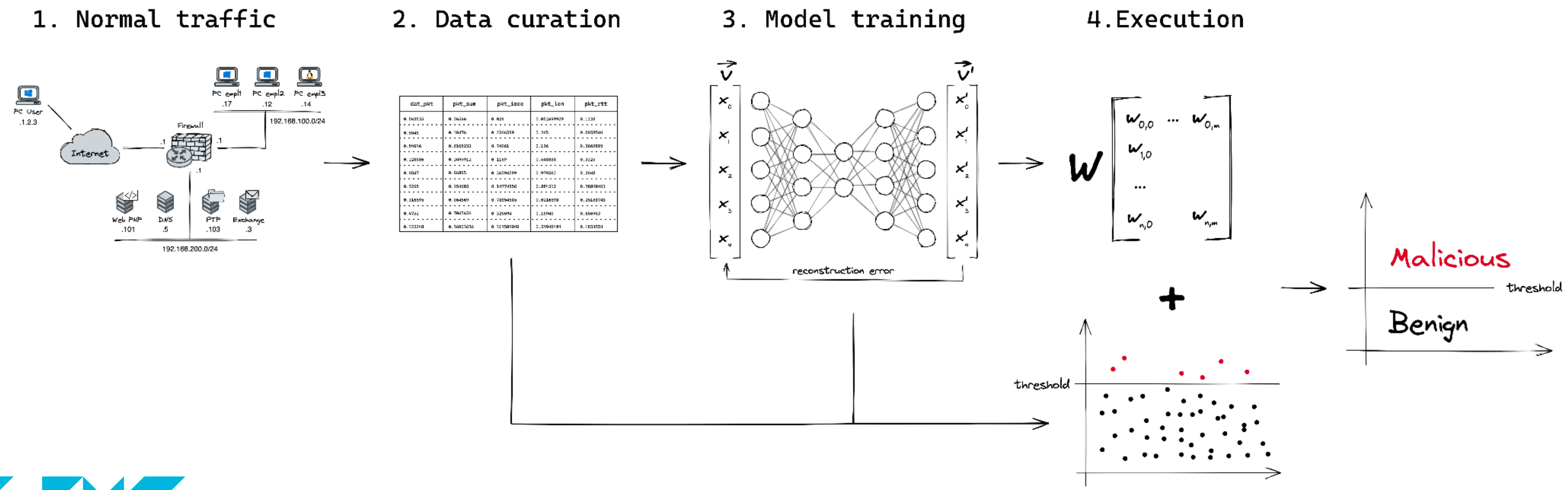
- **Different families:**
  - misuse detection, anomaly detection, specification-based…
- **Machine learning (ML) and deep learning (DL) often used for their performance**
  - *e.g.*, auto-encoder (AE) can be used for anomaly detection.
- **DL need a lot of data to be efficient, training them locally is a challenge**
  - *e.g.*, for AE, anything not known is an anomaly → higher false-positive rate.



- **Different families:**
  - misuse detection, anomaly detection, specification-based…
- **Machine learning (ML) and deep learning (DL) often used for their performance**
  - *e.g.*, auto-encoder (AE) can be used for anomaly detection.
- **DL need a lot of data to be efficient, training them locally is a challenge**
  - *e.g.*, for AE, anything not known is an anomaly → higher false-positive rate.



- **Different families:**
  - misuse detection, anomaly detection, specification-based…
- **Machine learning (ML) and deep learning (DL) often used for their performance**
  - *e.g.*, auto-encoder (AE) can be used for anomaly detection.
- **DL need a lot of data to be efficient, training them locally is a challenge**
  - *e.g.*, for AE, anything not known is an anomaly → higher false-positive rate.

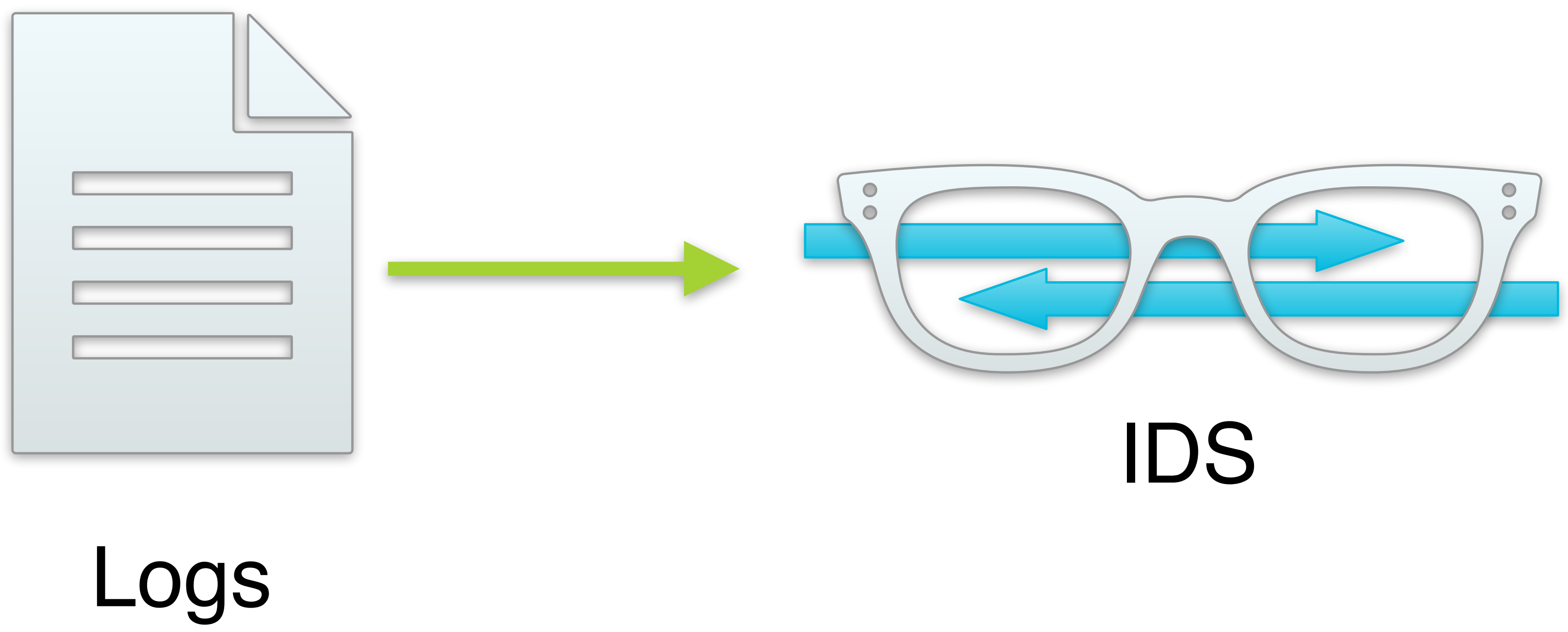


- **Intrusion Detection System (IDS)**
  & Security Information and Event Management (SIEM)
  - Individual alerts without context
  - Investigation leads analysts to alert fatigue

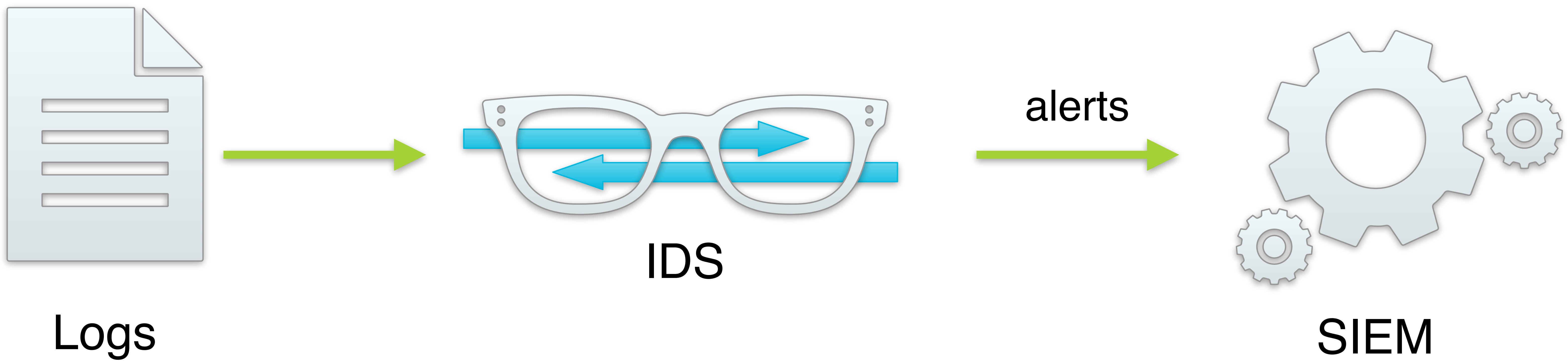
- **Intrusion Detection System (IDS)**
  & Security Information and Event Management (SIEM)
  - Individual alerts without context
  - Investigation leads analysts to alert fatigue

Logs

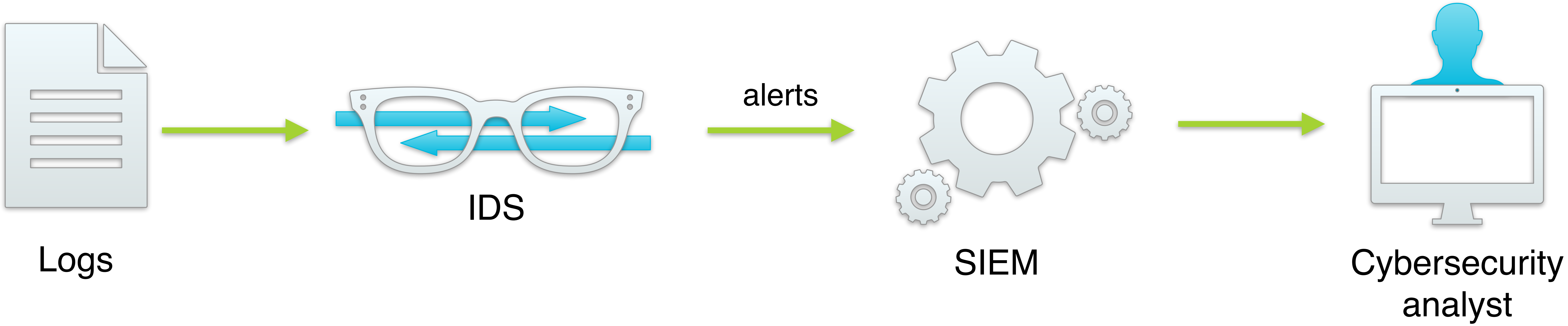
- **Intrusion Detection System (IDS) & Security Information and Event Management (SIEM)**
  - Individual alerts without context
  - Investigation leads analysts to alert fatigue



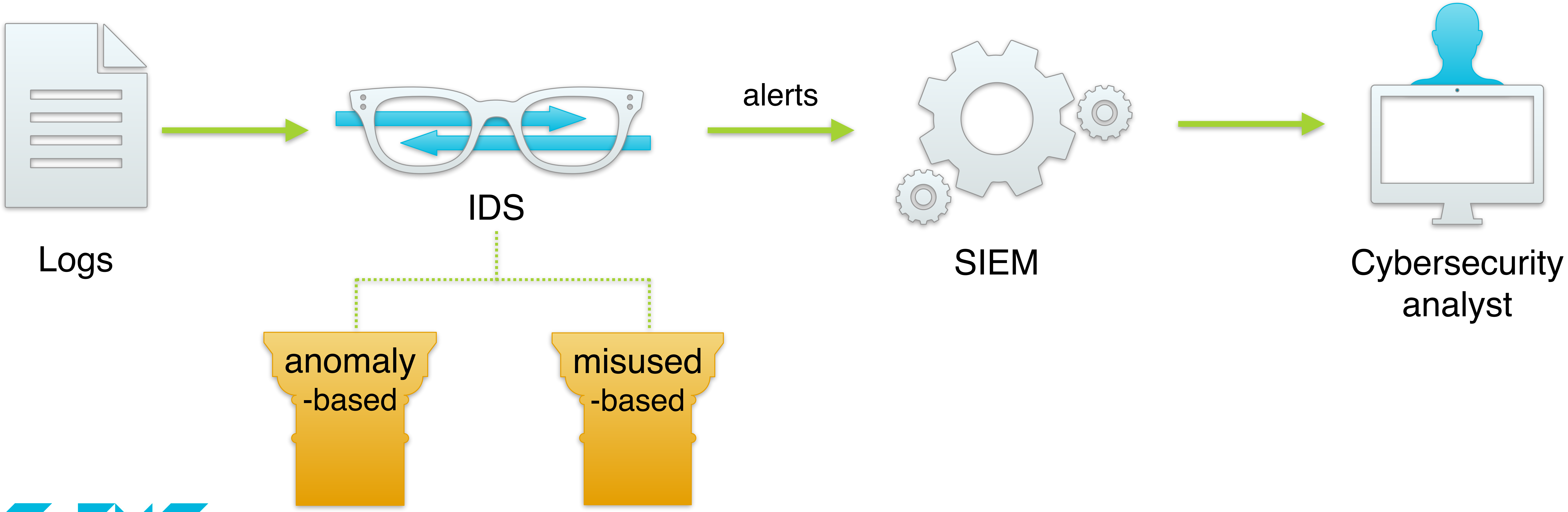
- **Intrusion Detection System (IDS)**
  & Security Information and Event Management (SIEM)
  - Individual alerts without context
  - Investigation leads analysts to alert fatigue



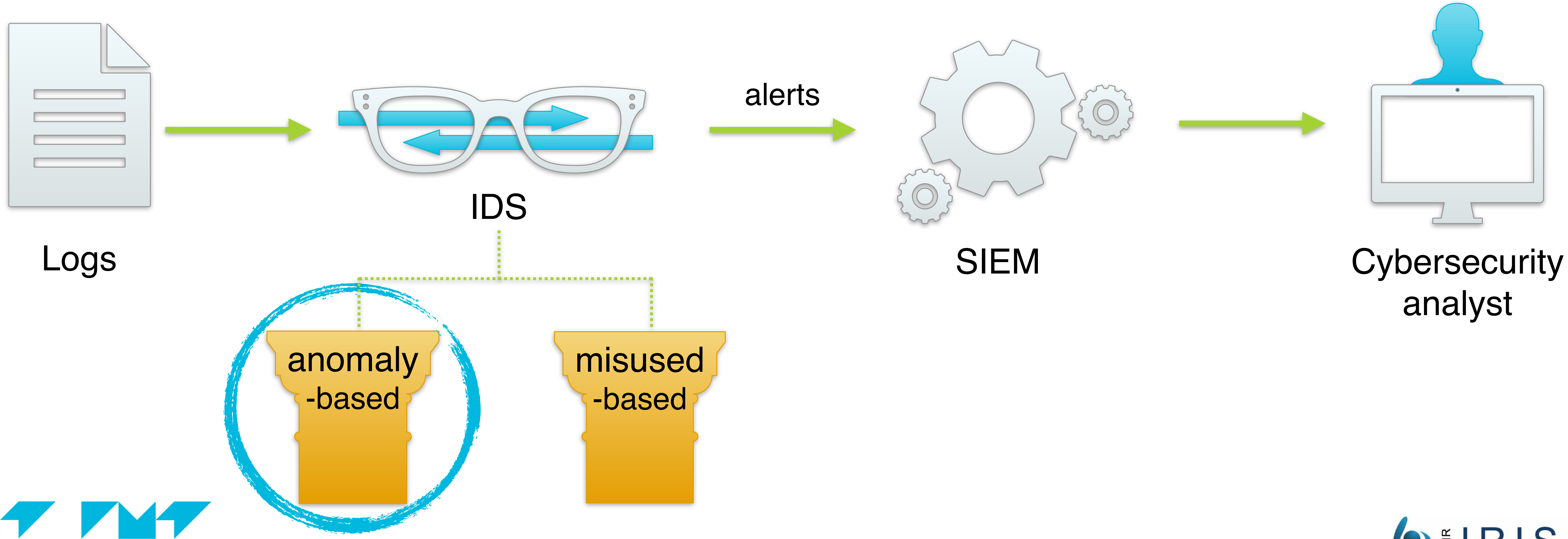
- **Intrusion Detection System (IDS)**
  & Security Information and Event Management (SIEM)
  - Individual alerts without context
  - Investigation leads analysts to alert fatigue



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



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



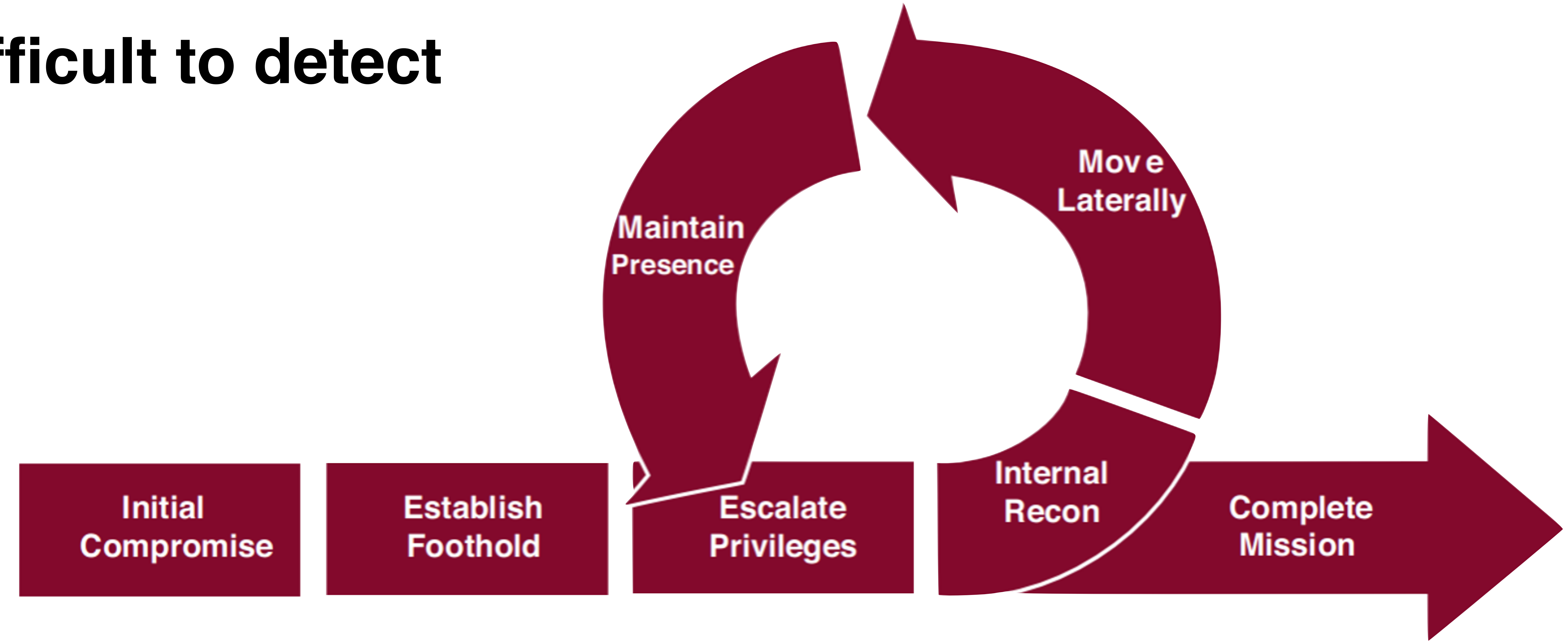
MULTI-STEP ATTACKS: EXTRACTION OF PROBABLE SCENARIOS BY CORRELATION OF ALERTS

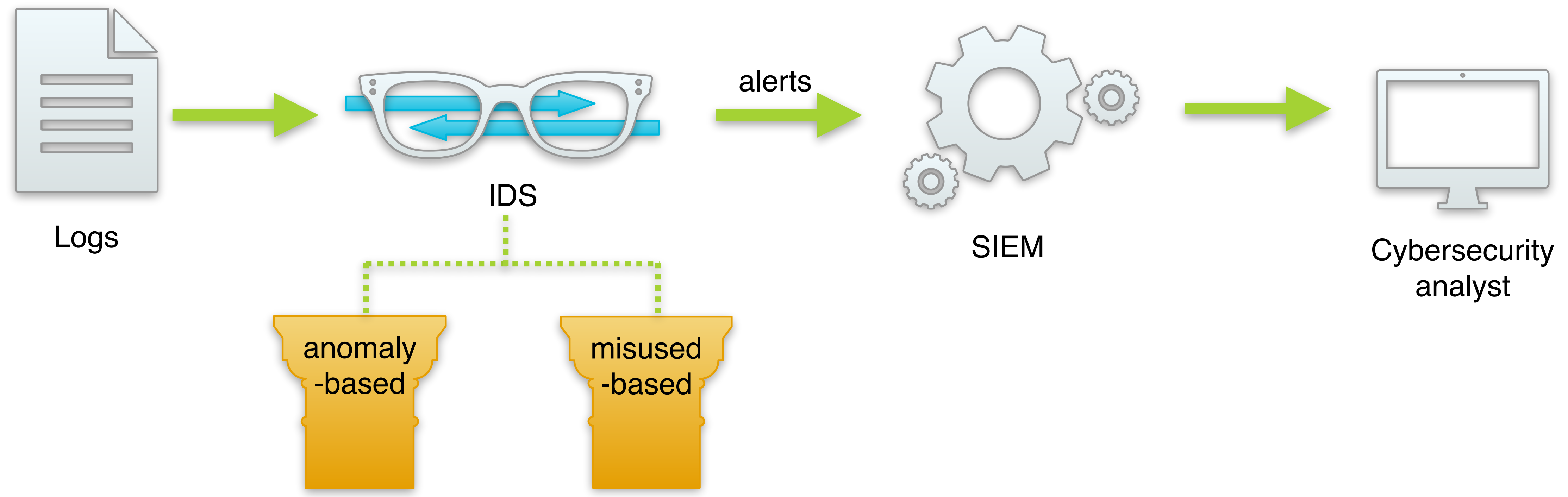
JOINT WORK WITH YANN BUSNEL (IMT NORD EUROPE)
ANTOINE REBSTOCK, ROMARIC LUDINARD (IMT ATLANTIQUE)
& STÉPHANE PAQUELET (IRT B<>COM)

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

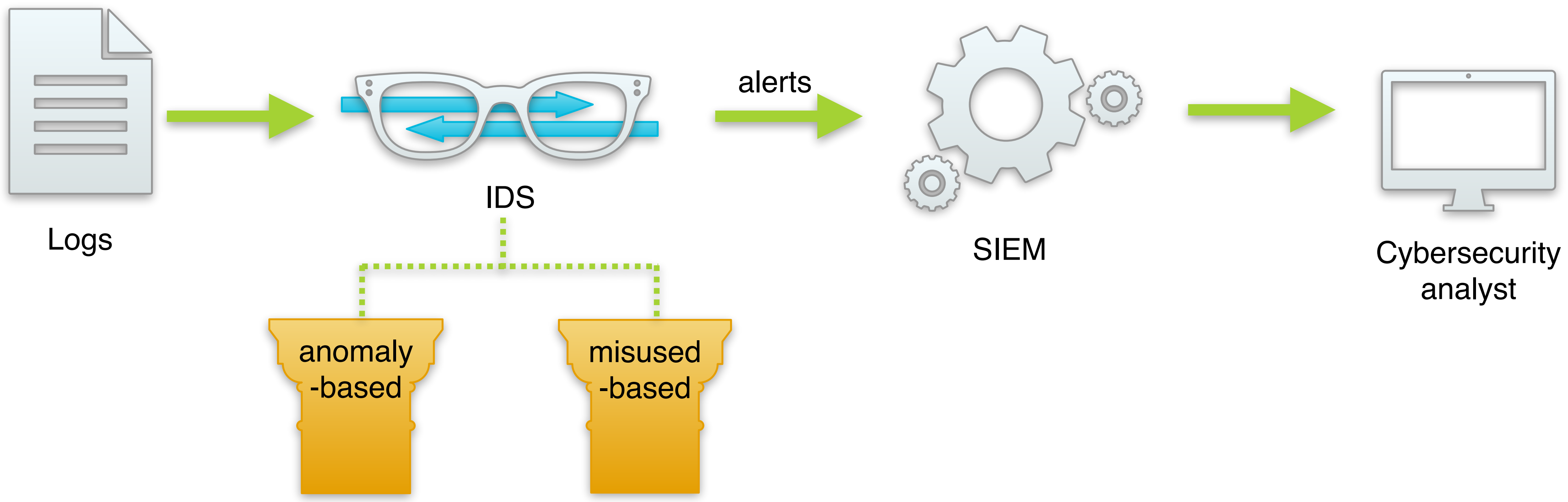
IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

- **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**




Logs
IDS
alerts
SIEM
Cybersecurity analyst
anomaly -based
misused -based

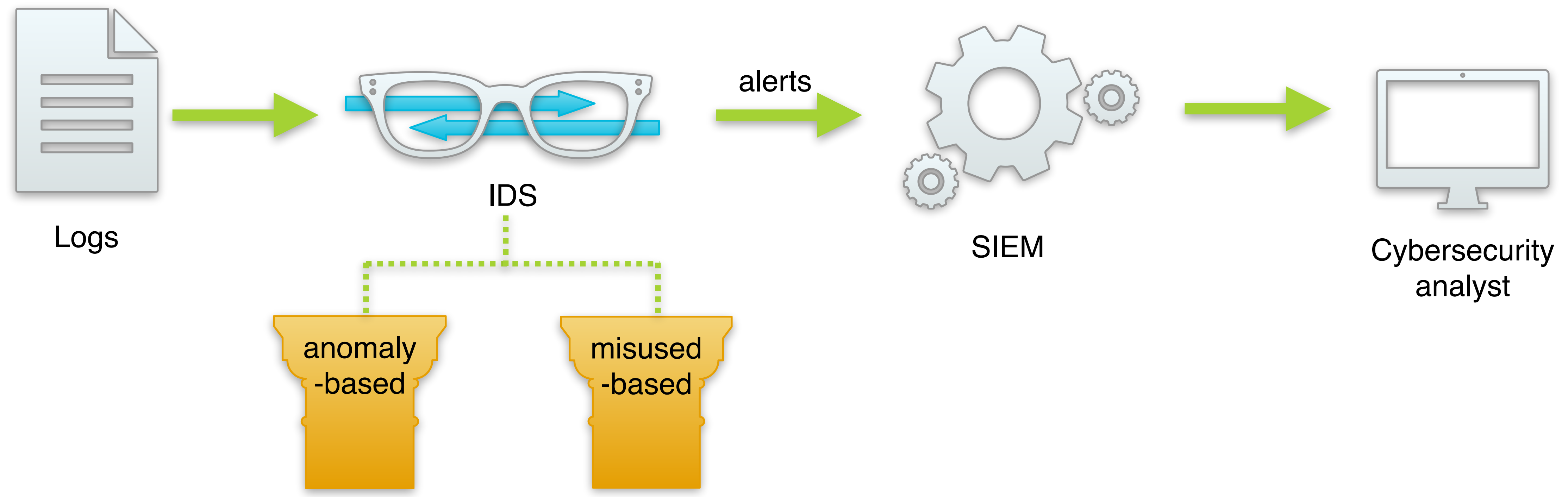
ON THE ROAD TO AUTOMATIC DETECTION



Analyst investigation

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

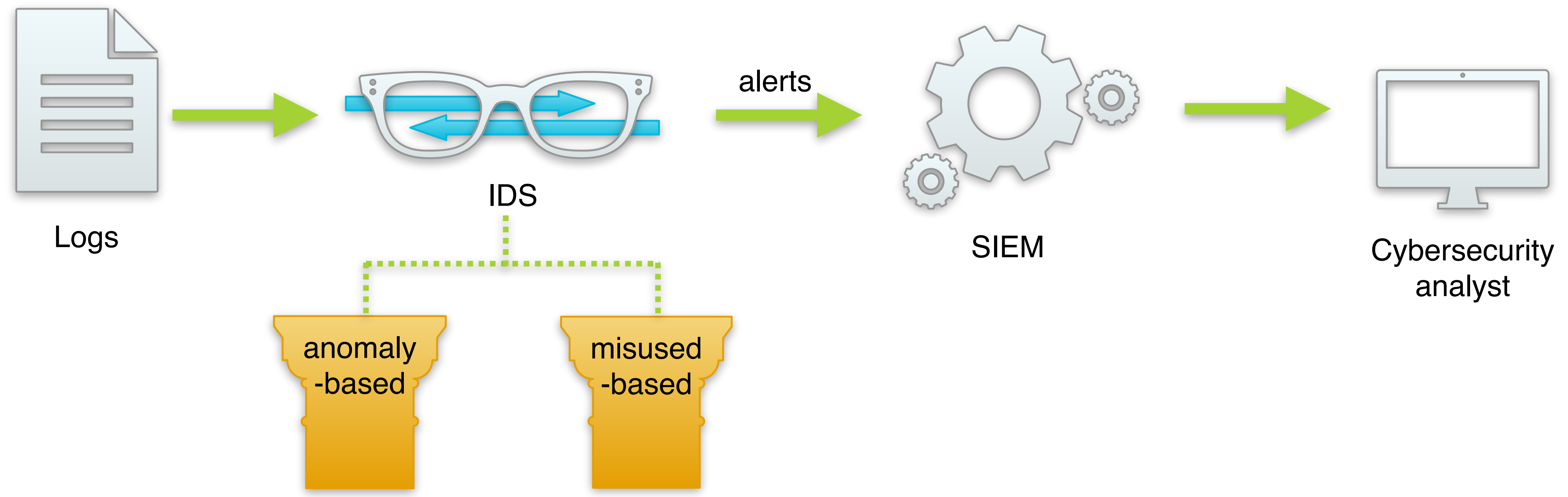
ON THE ROAD TO AUTOMATIC DETECTION



	Case-based
Human knowledge	✓
Unknown attacks detection	✗

Analyst investigation

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



	Case-based
Human knowledge	✓
Unknown attacks detection	✗

Stage 1

Analyst investigation

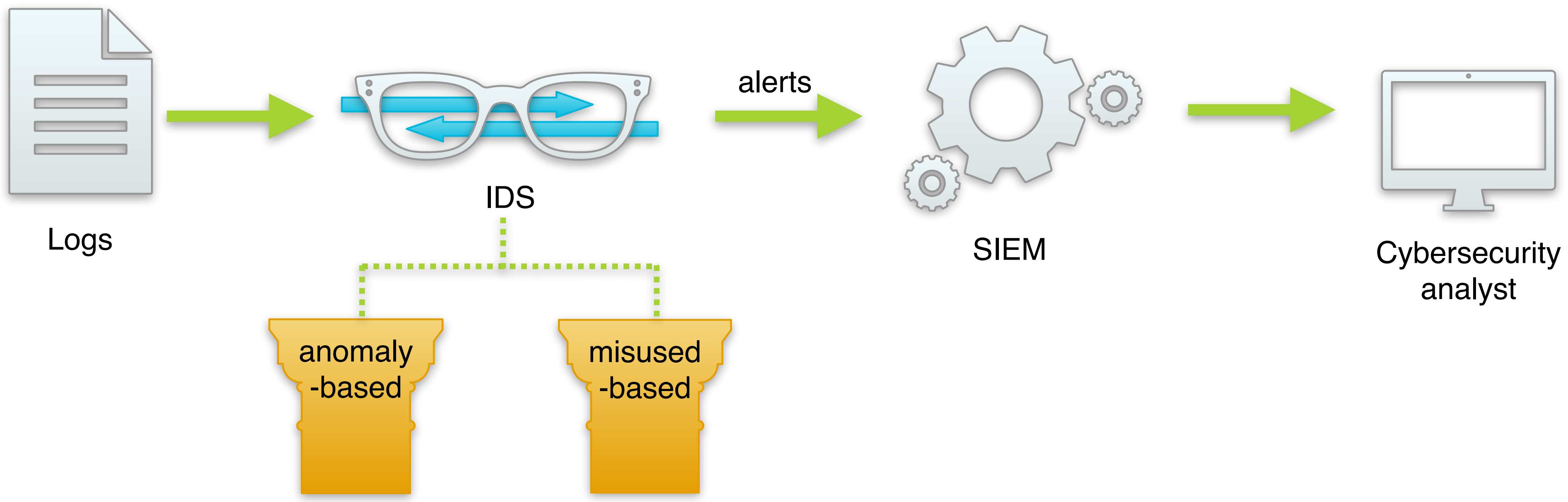
Current industrial approach uses IDS and SIEM to raise alerts that are later investigate by analyst

Stage 2

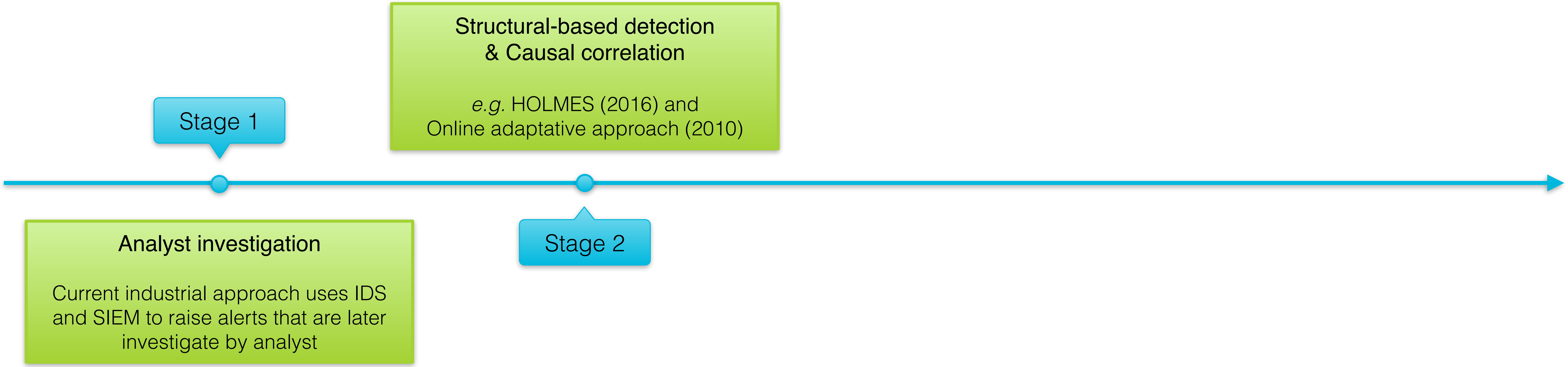
Structural-based detection & Causal correlation

e.g. HOLMES (2016) and Online adaptative approach (2010)

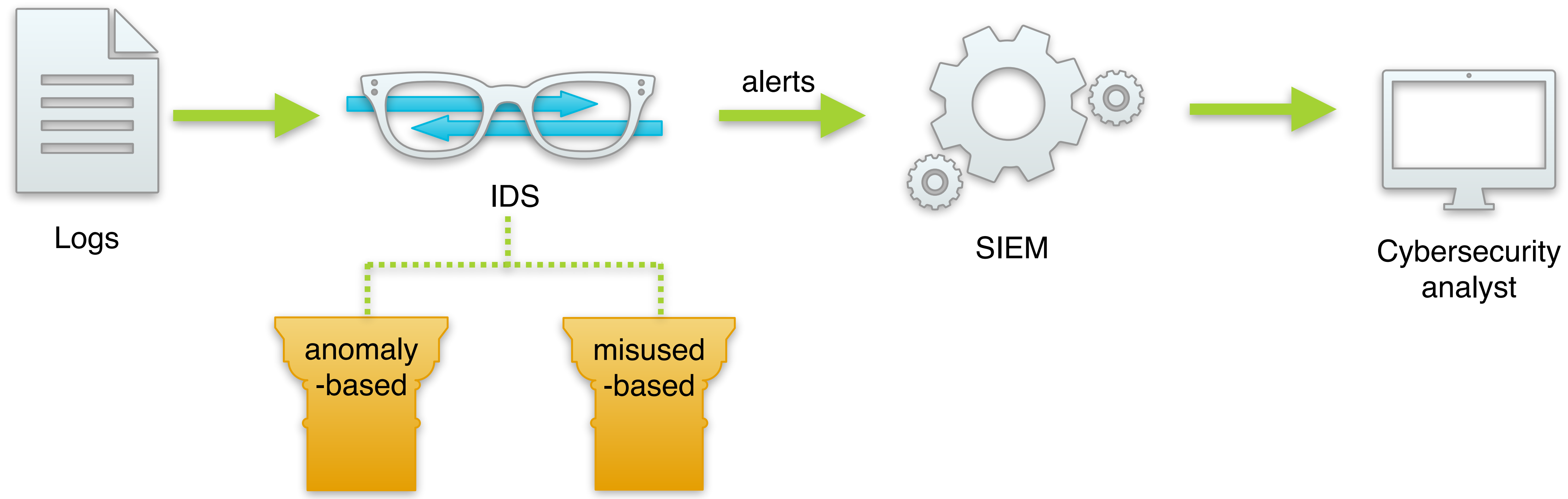
ON THE ROAD TO AUTOMATIC DETECTION



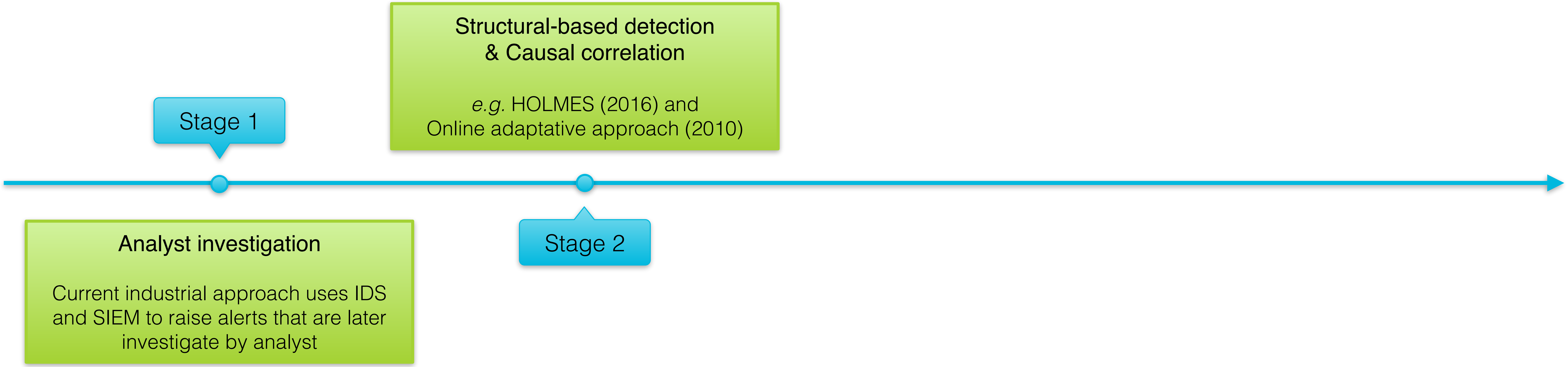
	Case-based	Structural-based
Human knowledge	✓	✓
Unknown attacks detection	✗	✗



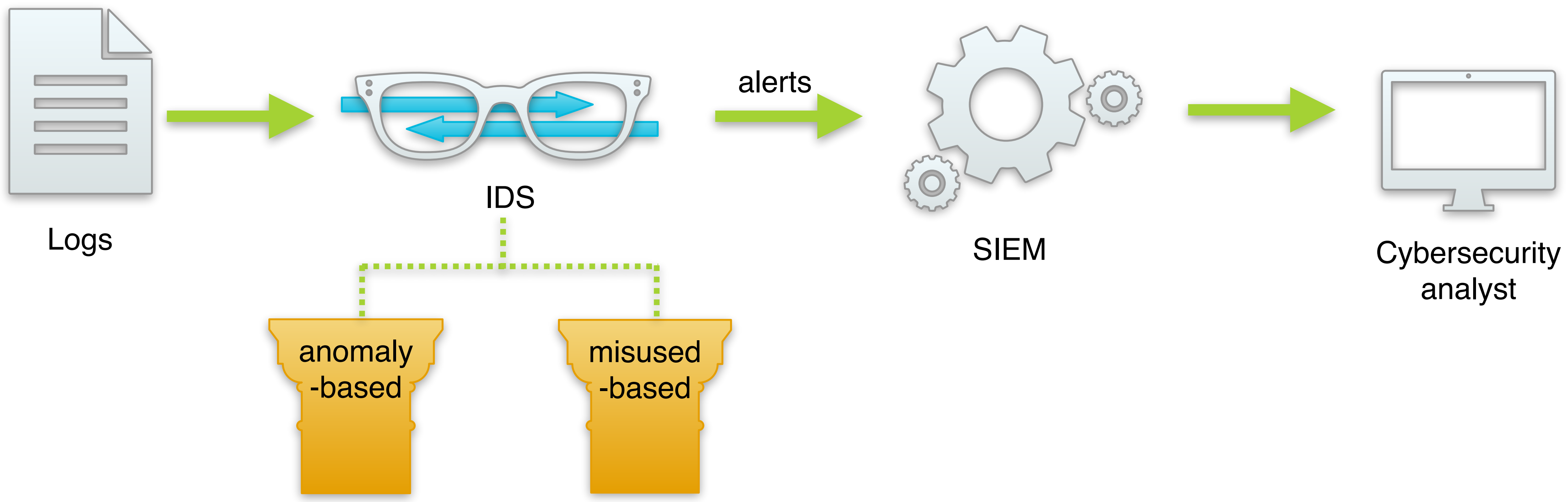
ON THE ROAD TO AUTOMATIC DETECTION



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



ON THE ROAD TO AUTOMATIC DETECTION



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

Stage 1

Analyst investigation

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

Stage 2

Structural-based detection & Causal correlation

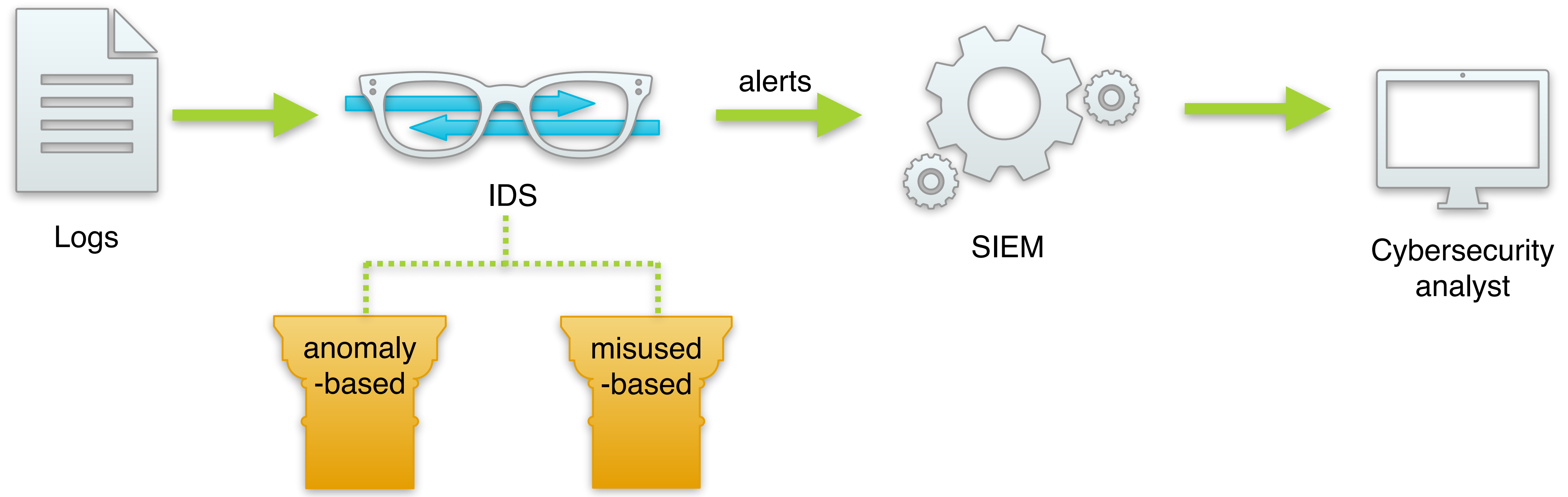
e.g. HOLMES (2016) and Online adaptative approach (2010)

Stage 3

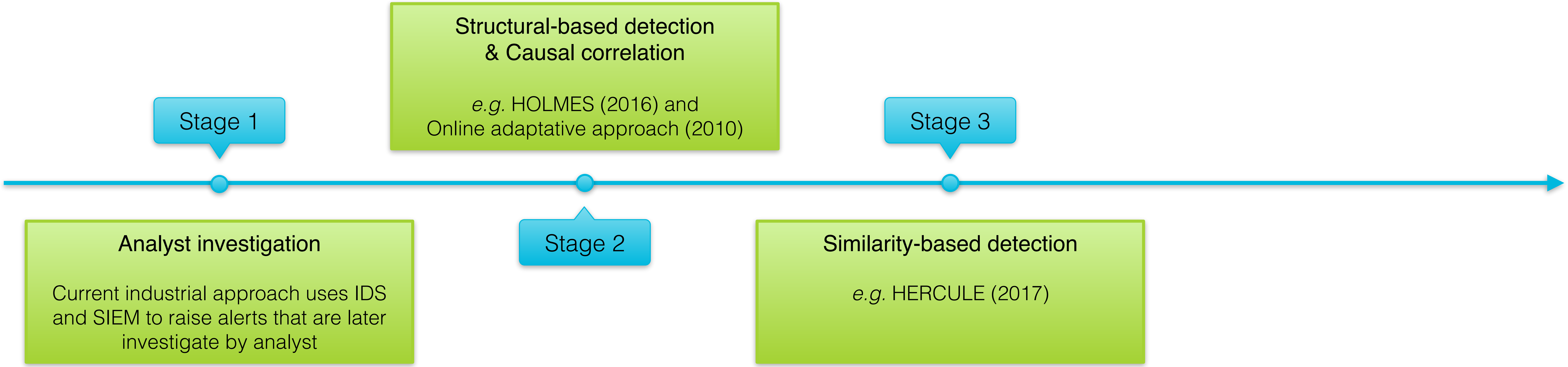
Similarity-based detection

e.g. HERCULE (2017)

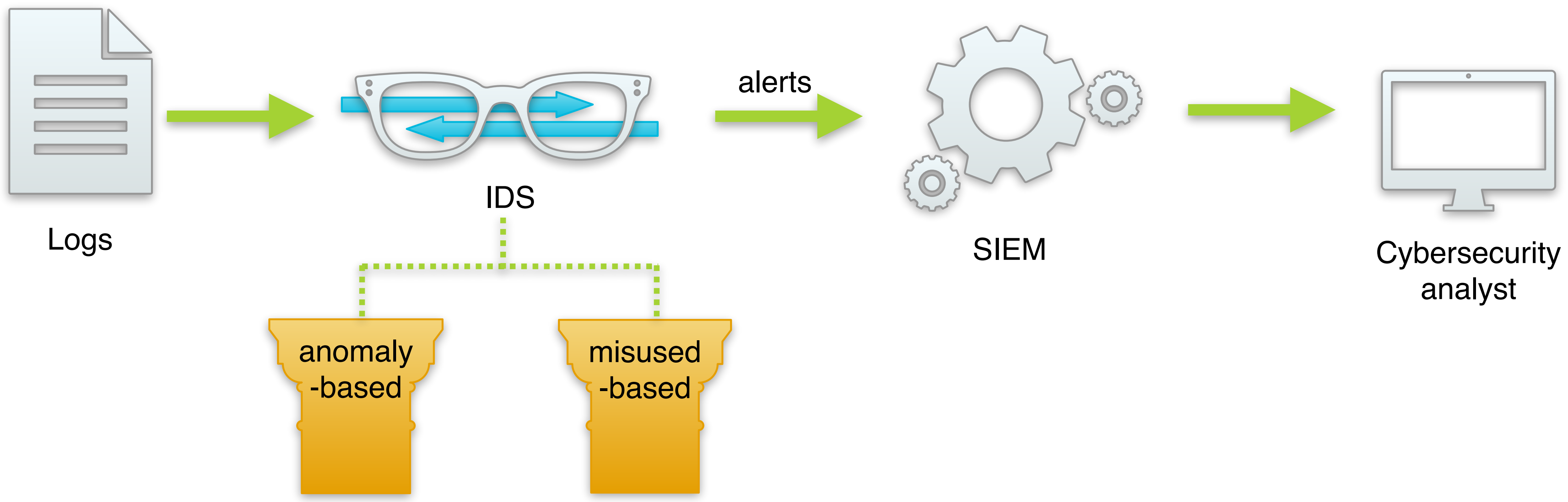
ON THE ROAD TO AUTOMATIC DETECTION



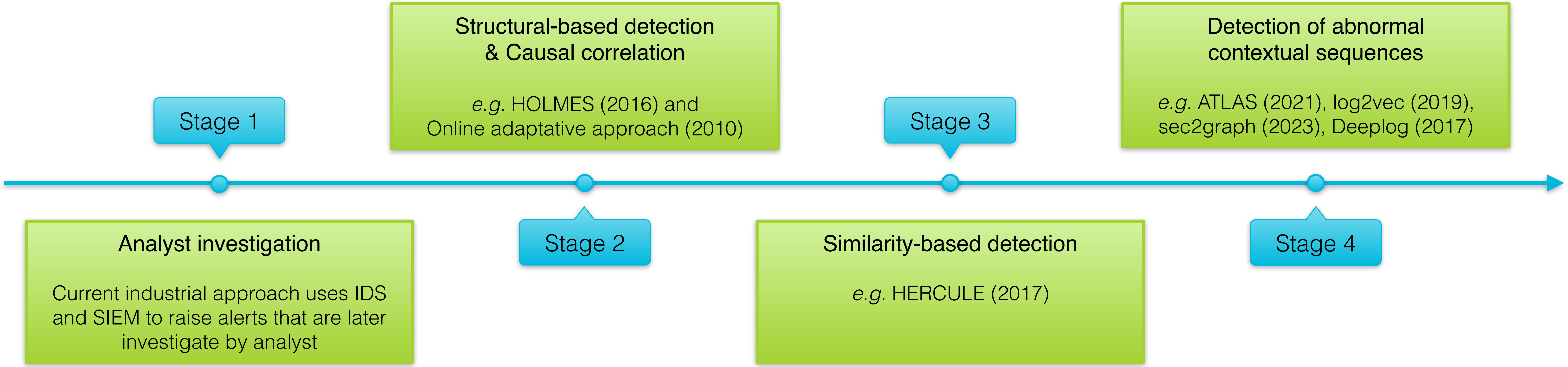
	Case-based	Structural-based	Causal correlation	Similarity-based
Human knowledge	✓	✓	✗	✗
Unknown attacks detection	✗	✗	Only light variations	✓



ON THE ROAD TO AUTOMATIC DETECTION

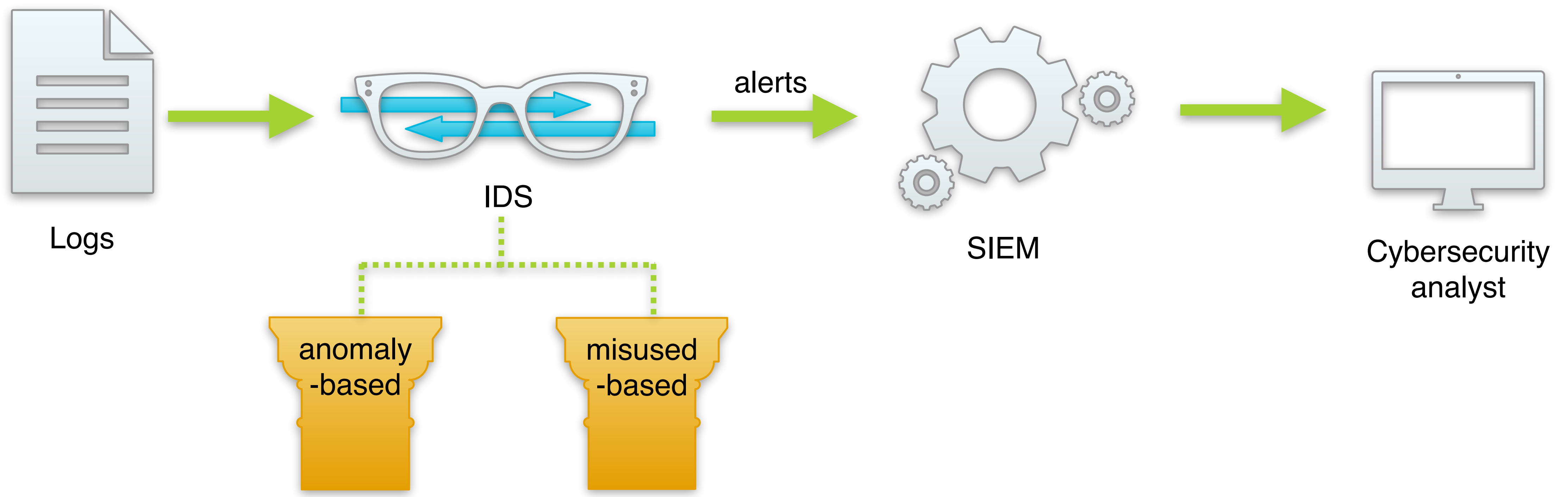


	Case-based	Structural-based	Causal correlation	Similarity-based
Human knowledge	✓	✓	✗	✗
Unknown attacks detection	✗	✗	Only light variations	✓

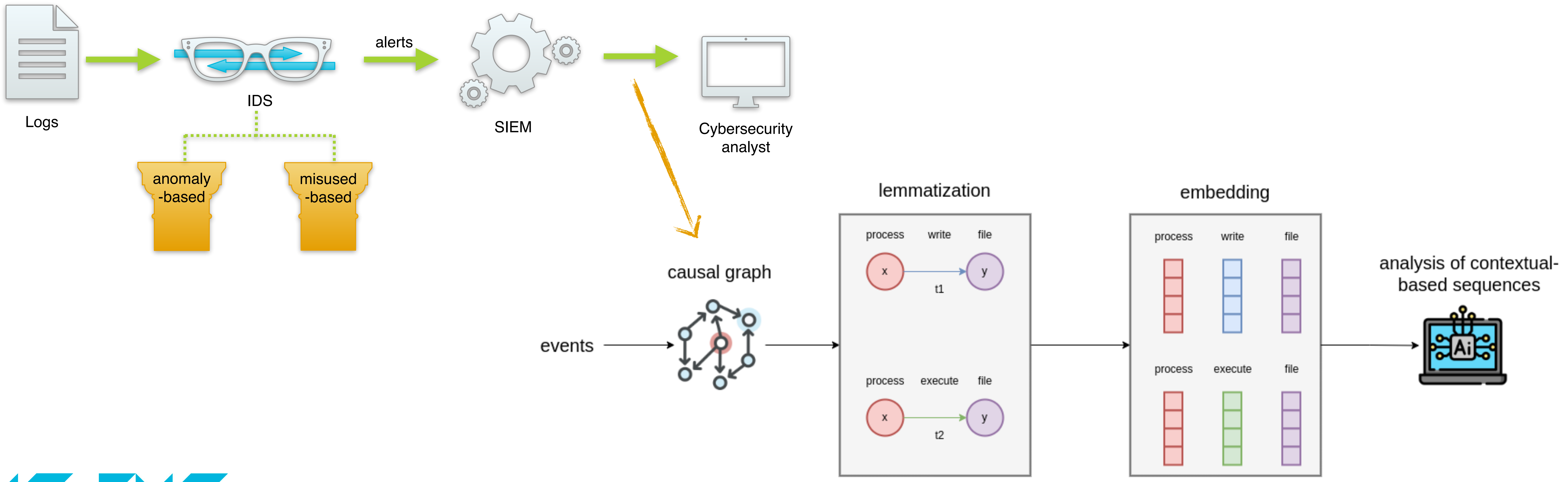


Decision support

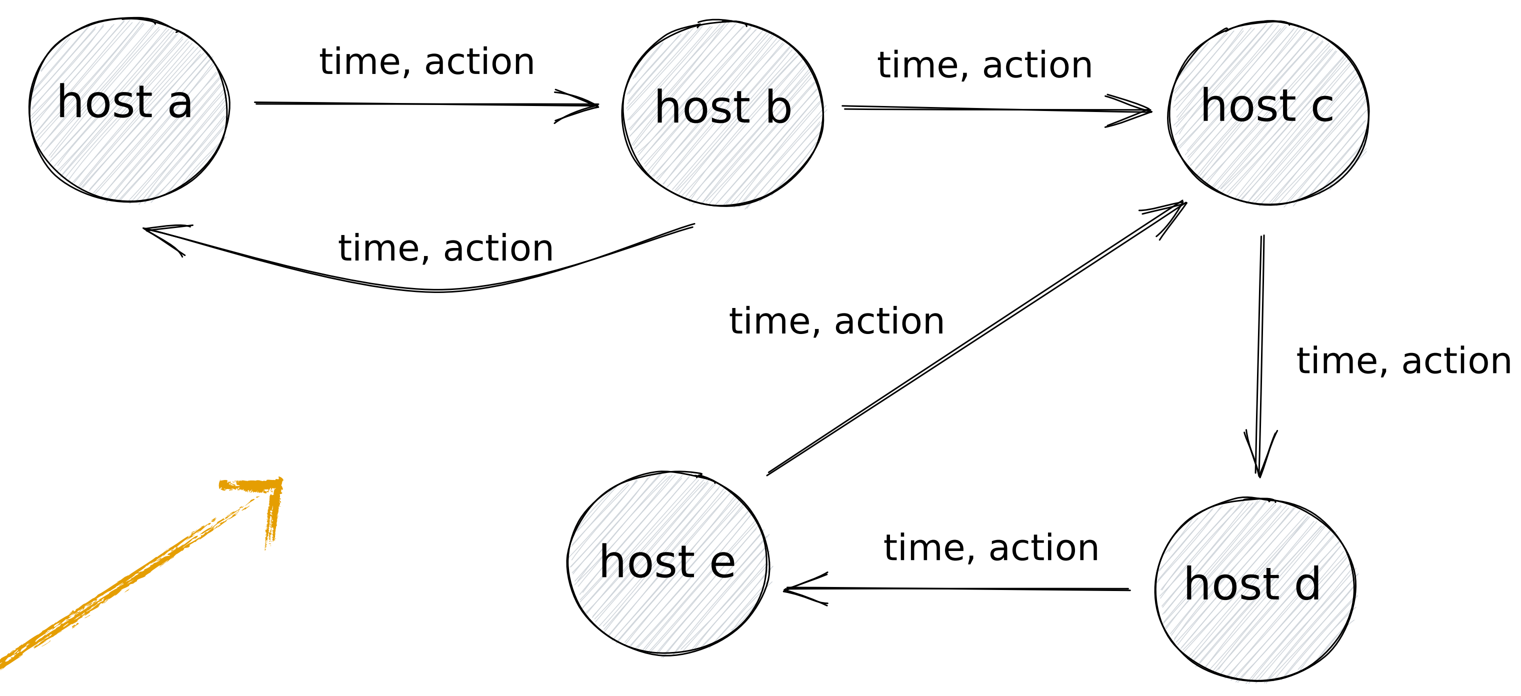
- Sequences of contextual events
- Highlight abnormal sequences of events
- Reduce alert fatigue and detects discrete behaviors

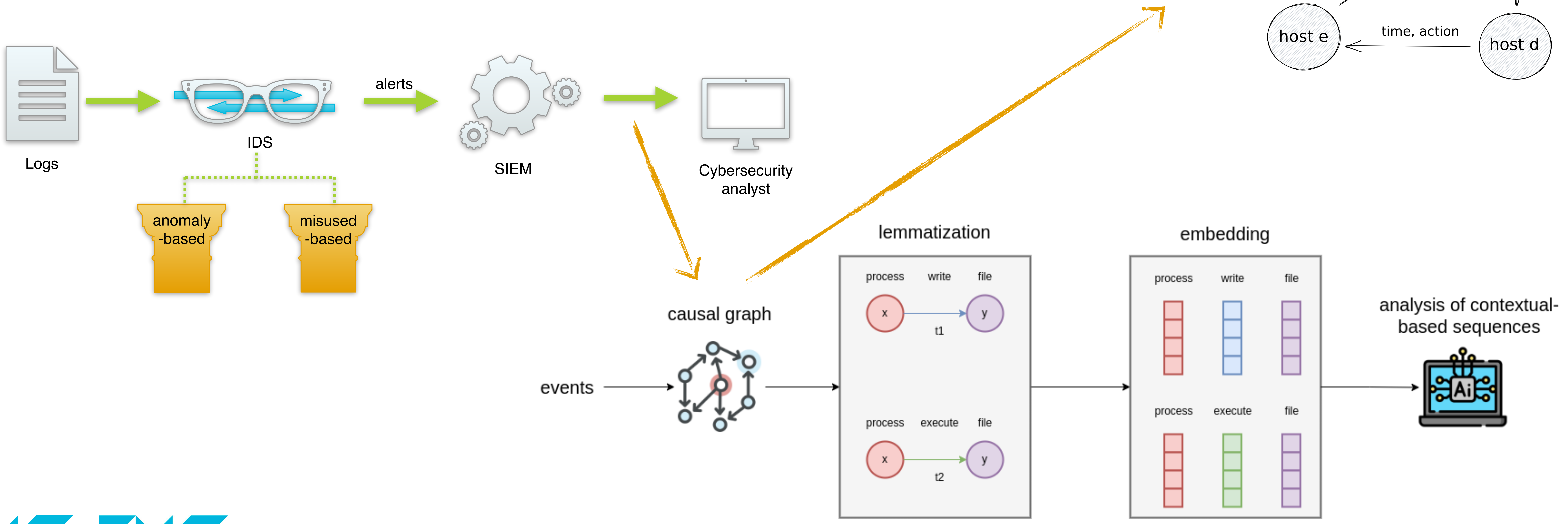


- **Decision support**
  - Sequences of contextual events
  - Highlight abnormal sequences of events
  - Reduce alert fatigue and detects discrete behaviors



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





FEDERATED LEARNING APPROACHES FOR DEFENDING AND DETECTING CYBER-ATTACKS

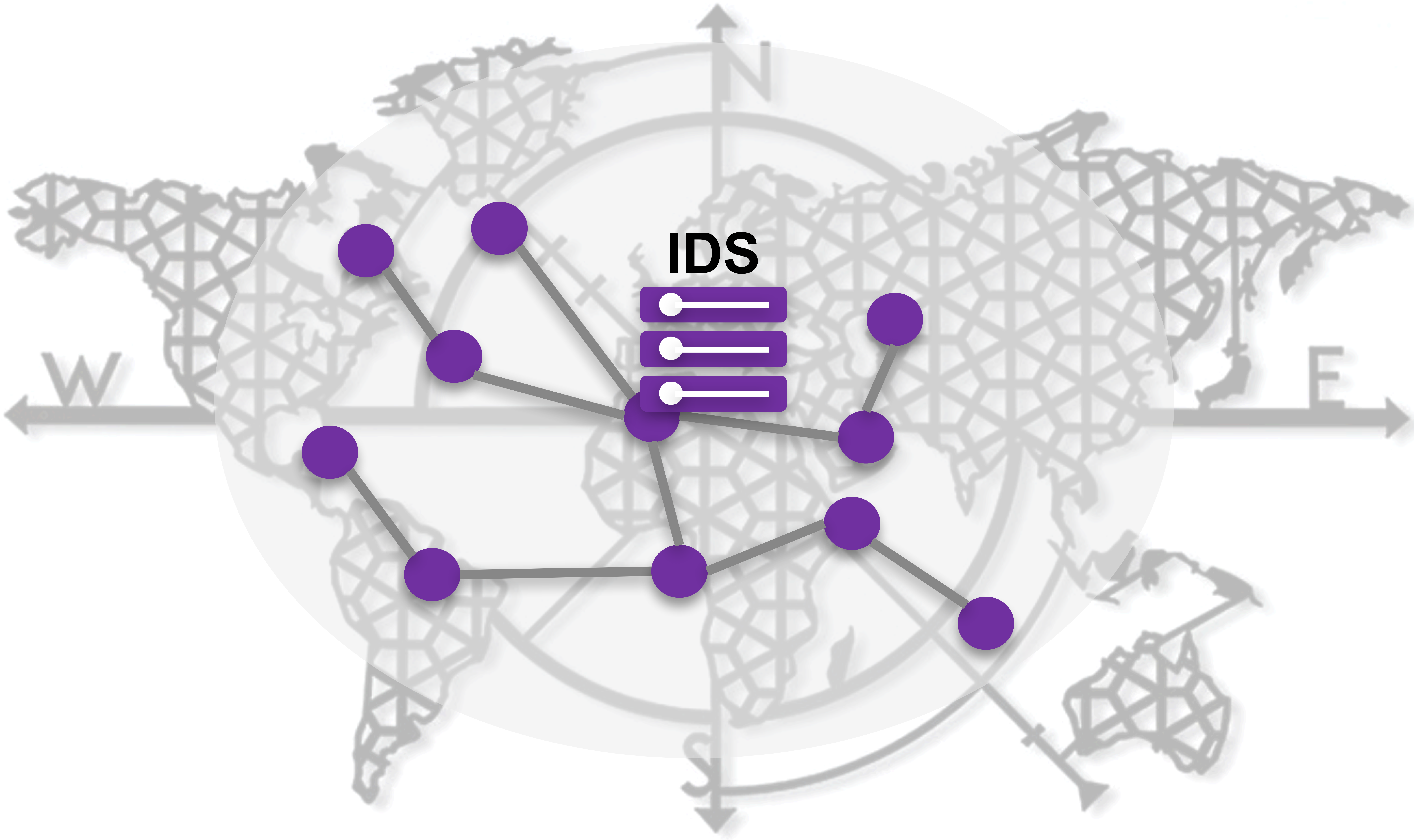
JOINT WORK WITH YANN BUSNEL (IMT NORD EUROPE)
LEO LAVAUR, FABIEN AUTREL, AND MARC-OLIVER PAHL (IMT ATLANTIQUE)

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

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

SECURITY MONITORING

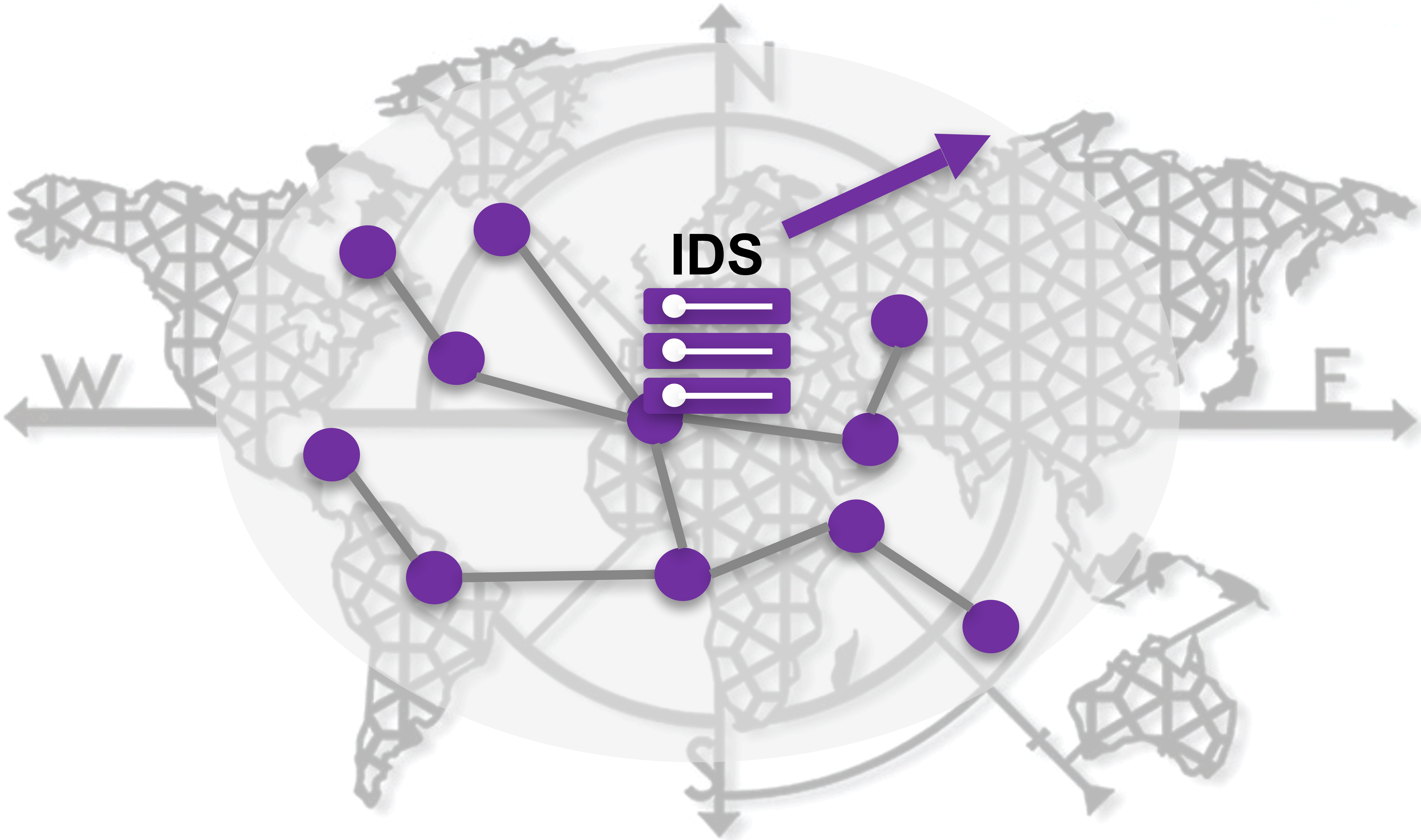
Cyberattack detection in infrastructures



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

SECURITY MONITORING

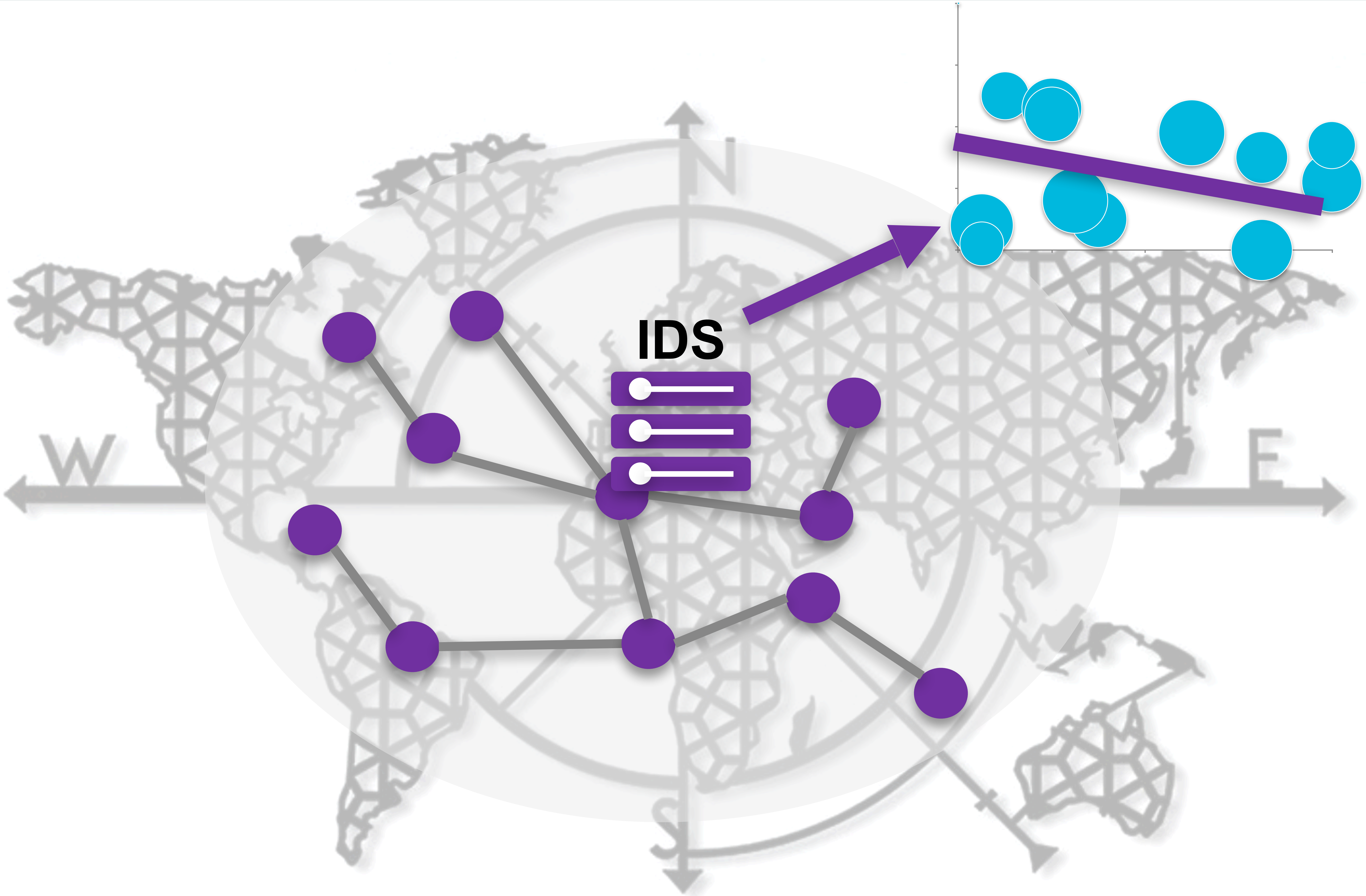
Cyberattack detection in infrastructures



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

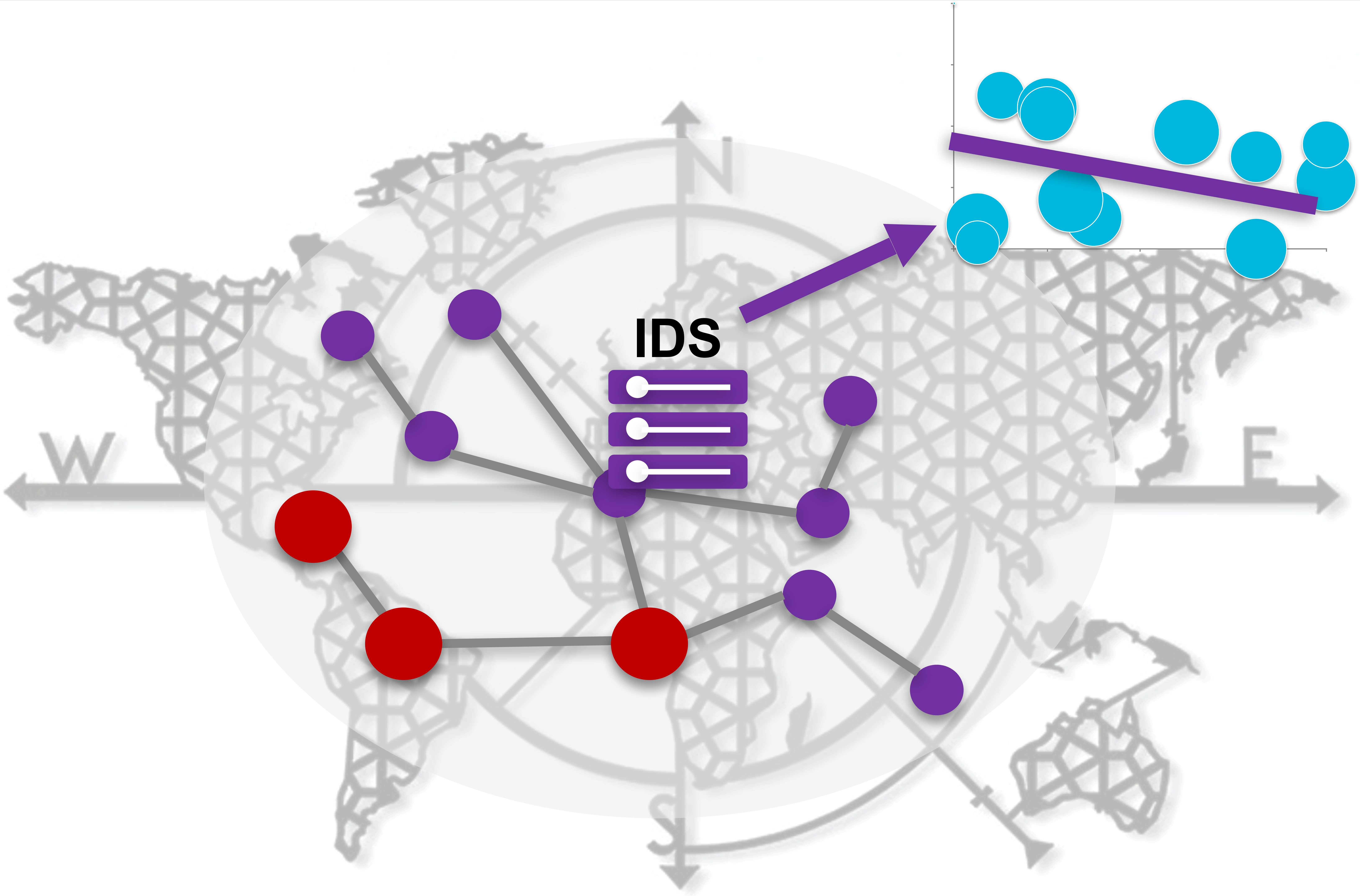
SECURITY MONITORING

Cyberattack detection in infrastructures



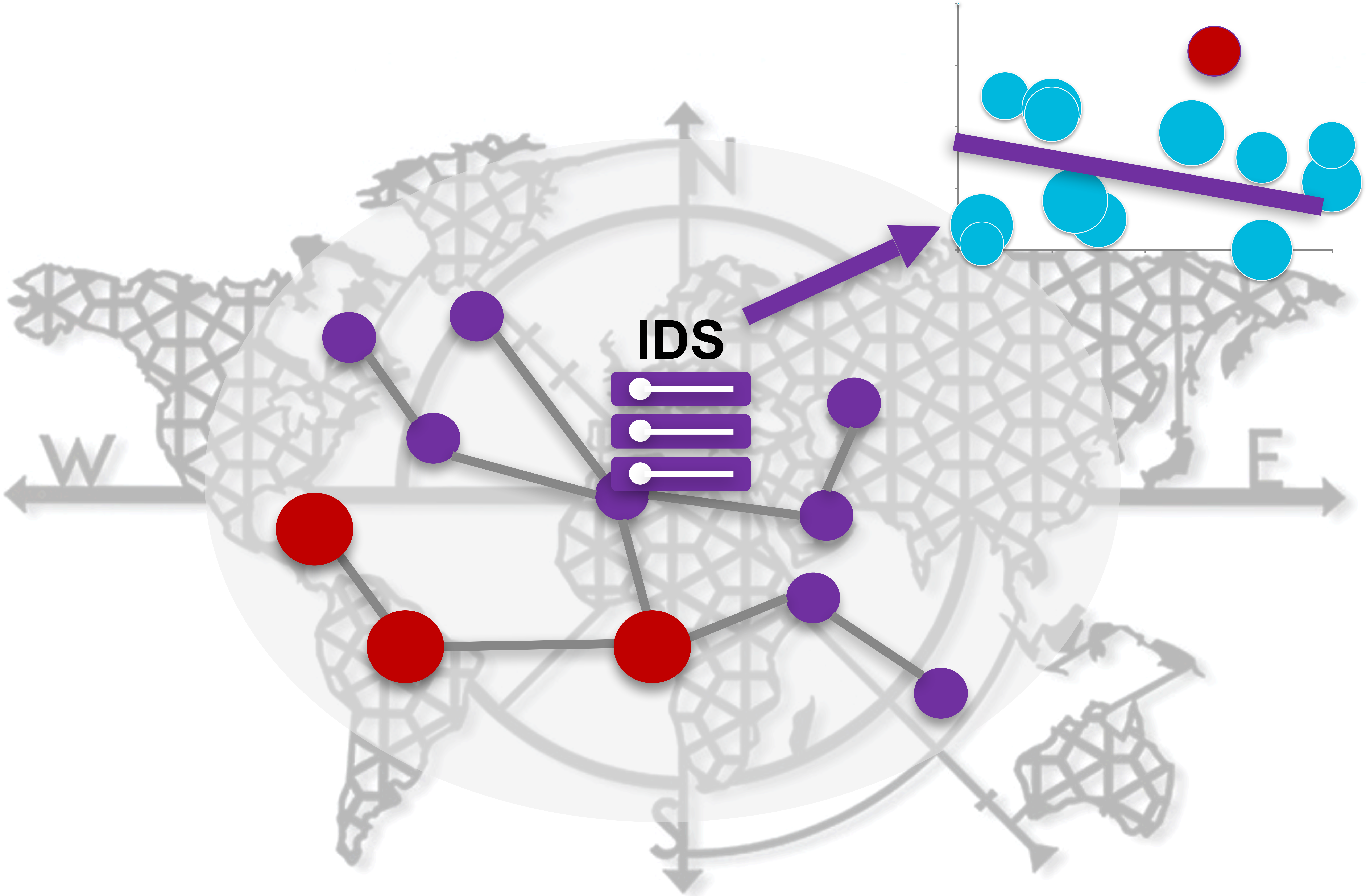
IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

SECURITY MONITORING
Cyberattack detection in infrastructures



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

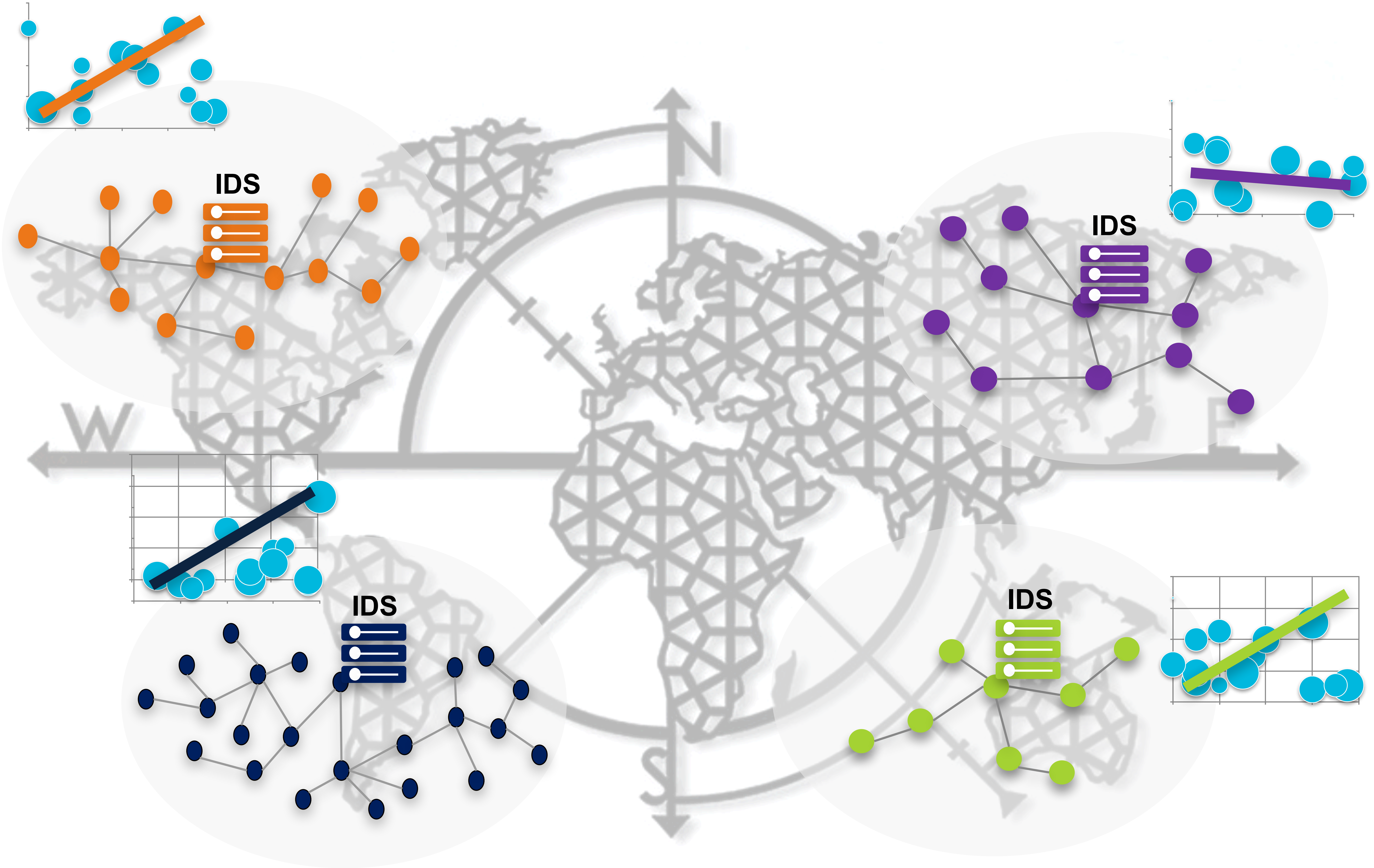
SECURITY MONITORING
Cyberattack detection in infrastructures



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

AT MULTIPLE ORGANISATION SCALE

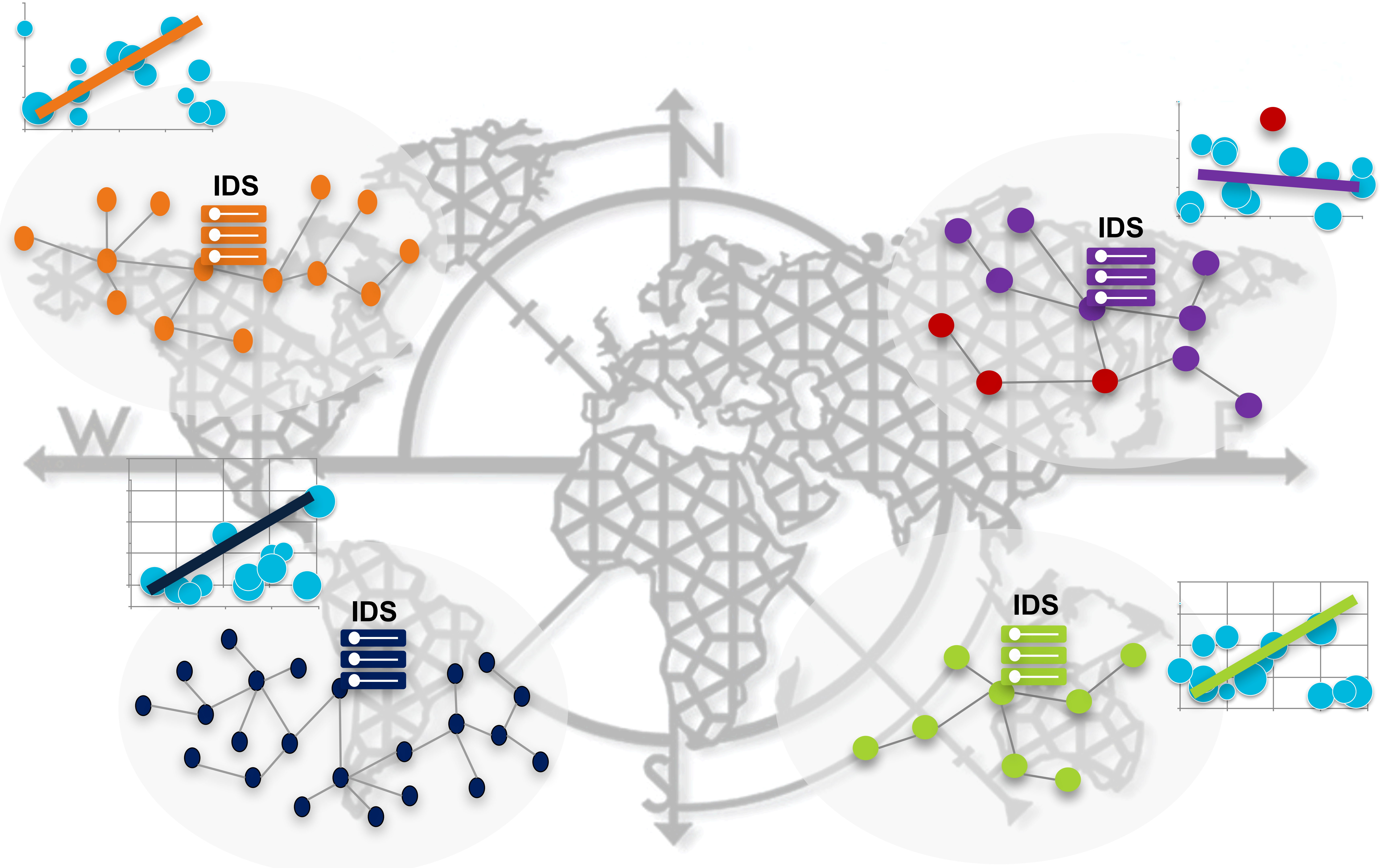
How to share experience in intrusion detection?



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

AT MULTIPLE ORGANISATION SCALE

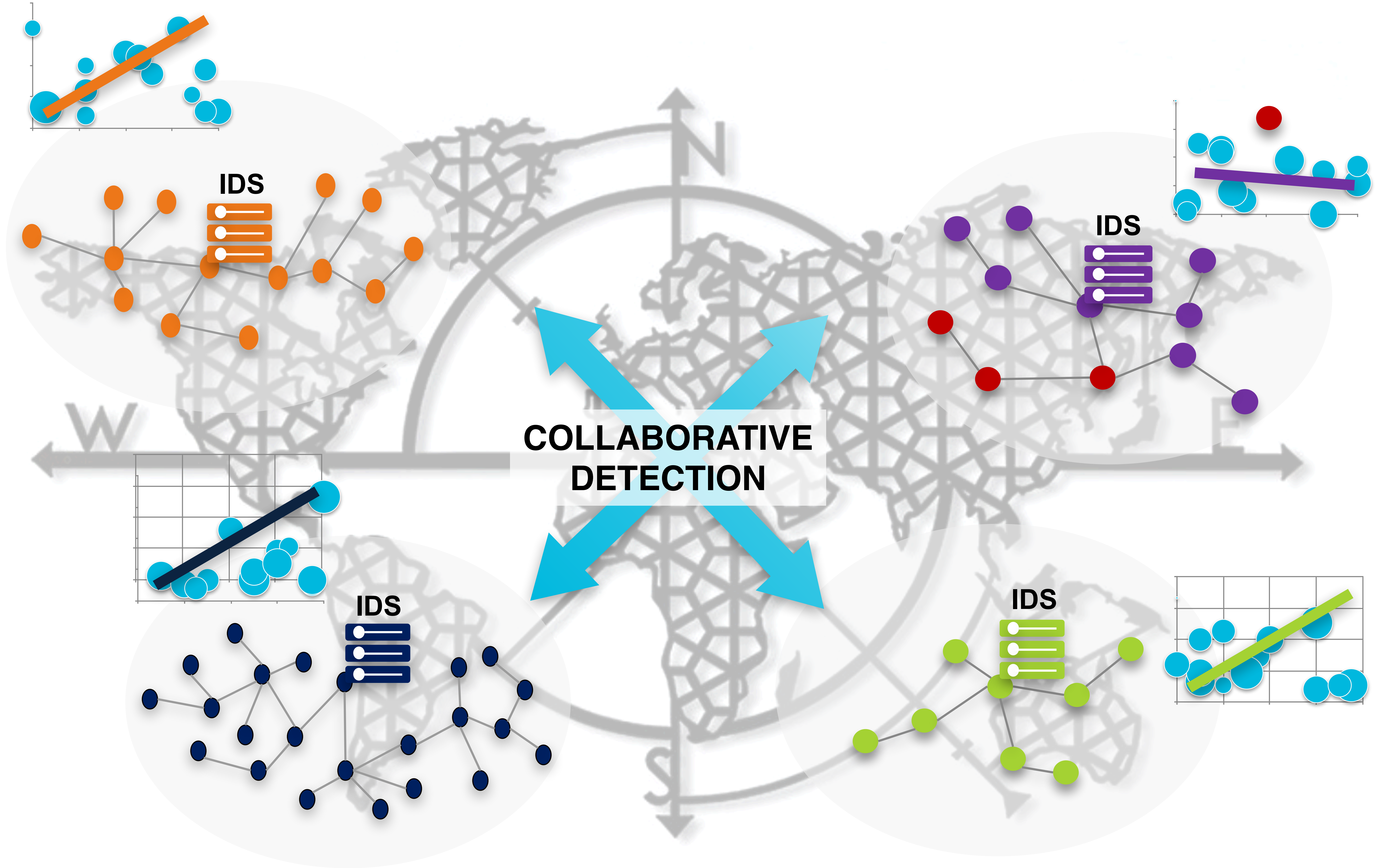
How to share experience in intrusion detection?



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

AT MULTIPLE ORGANISATION SCALE

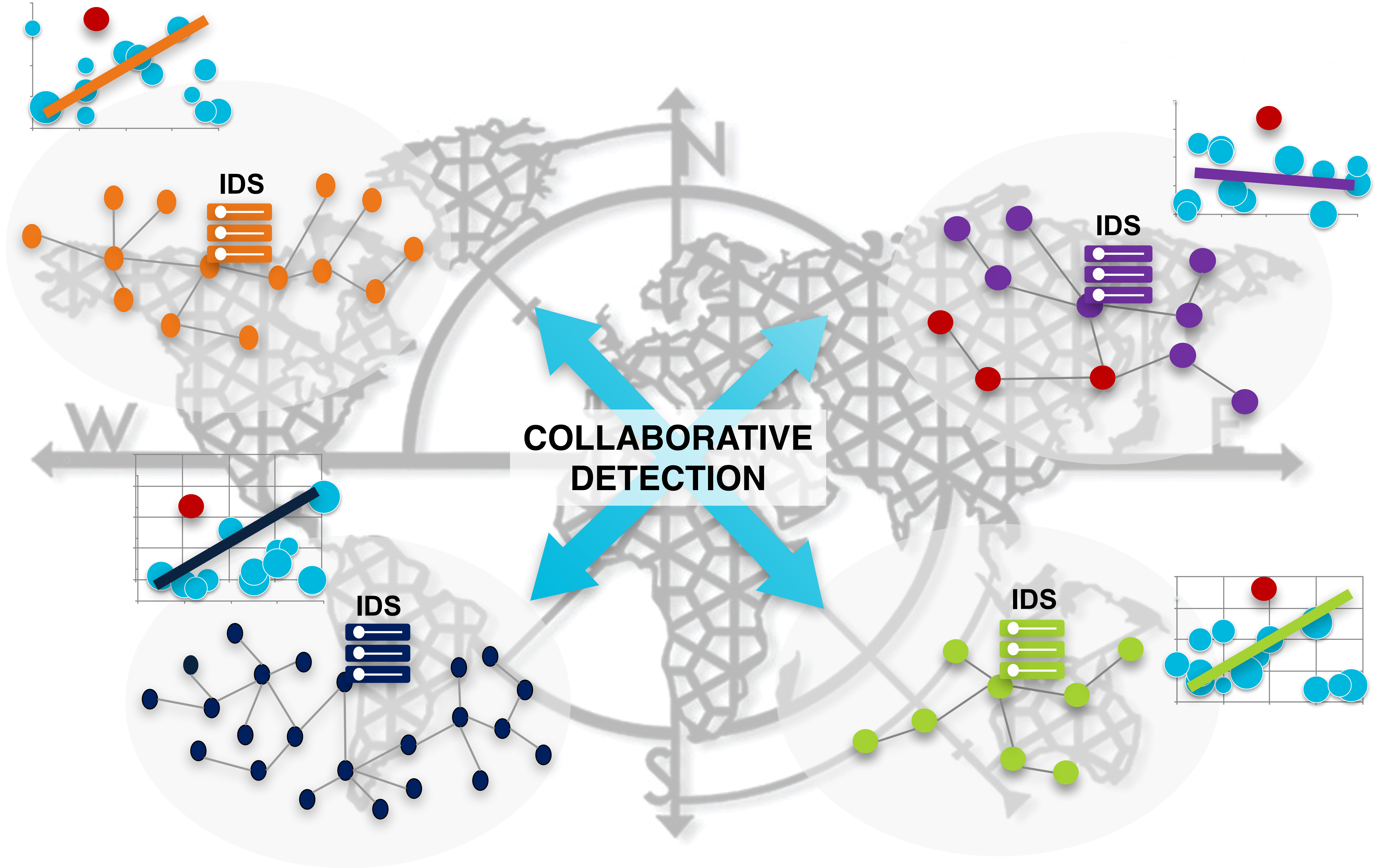
How to share experience in intrusion detection?



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

AT MULTIPLE ORGANISATION SCALE

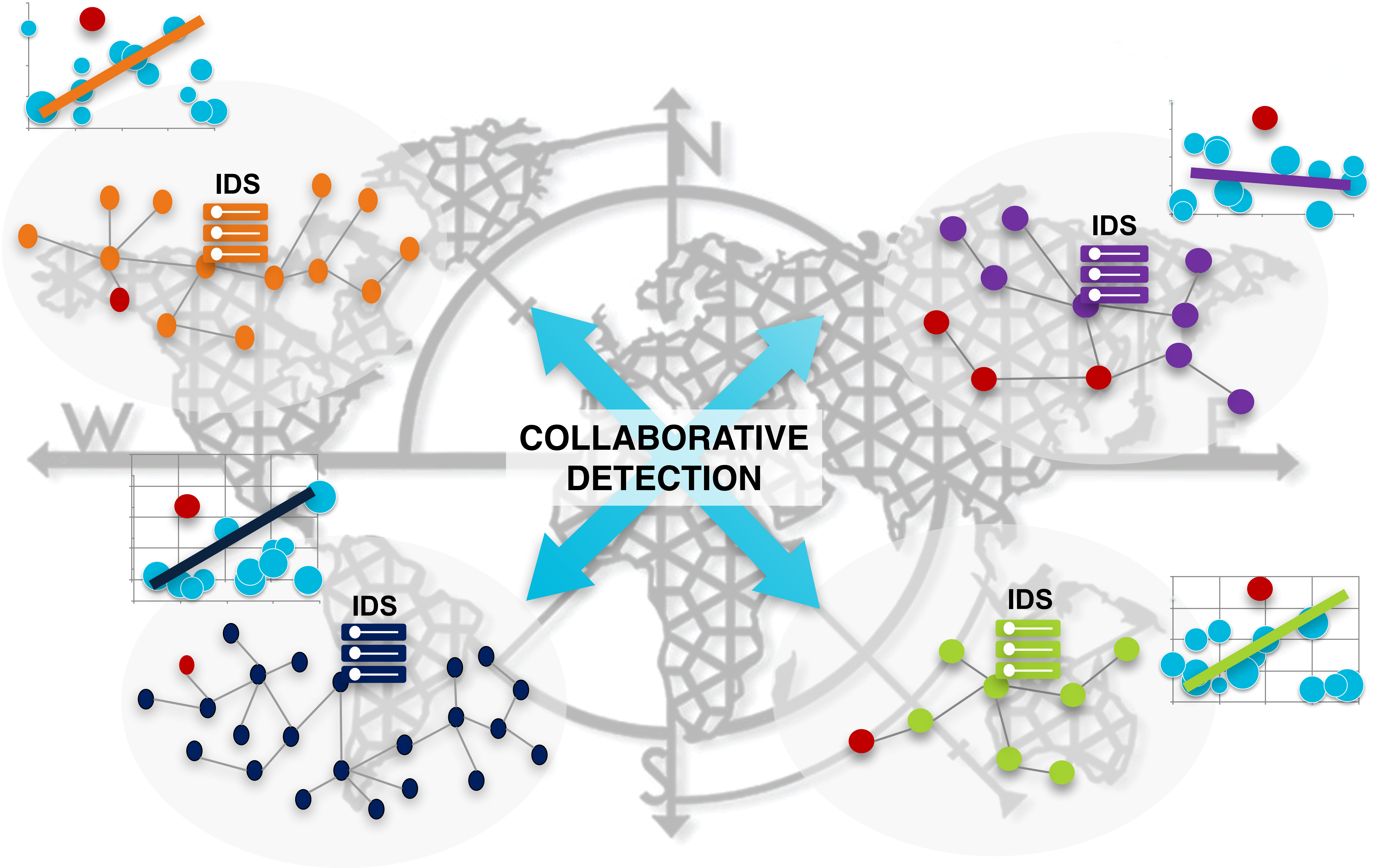
How to share experience in intrusion detection?



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

AT MULTIPLE ORGANISATION SCALE

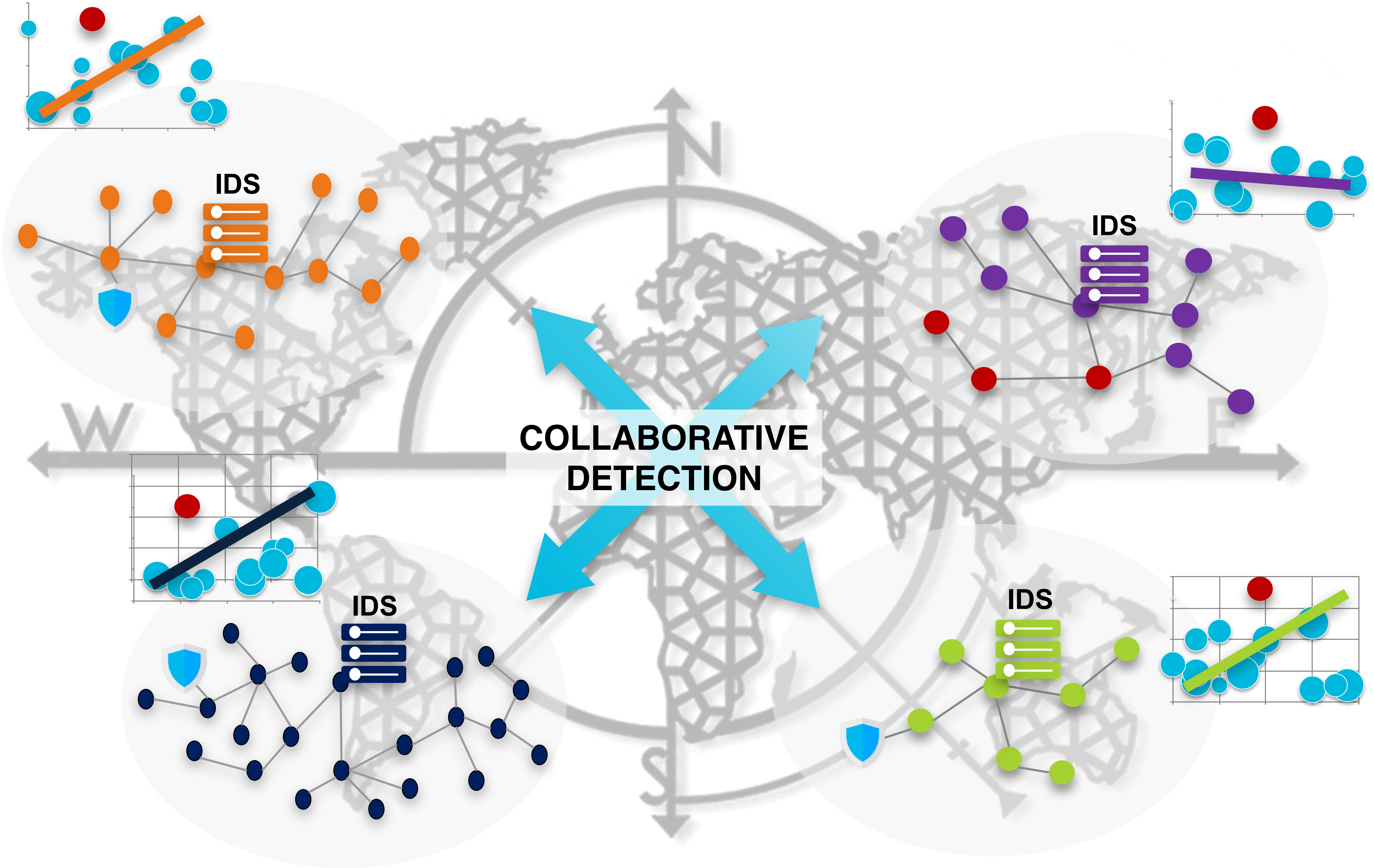
How to share experience in intrusion detection?



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

AT MULTIPLE ORGANISATION SCALE

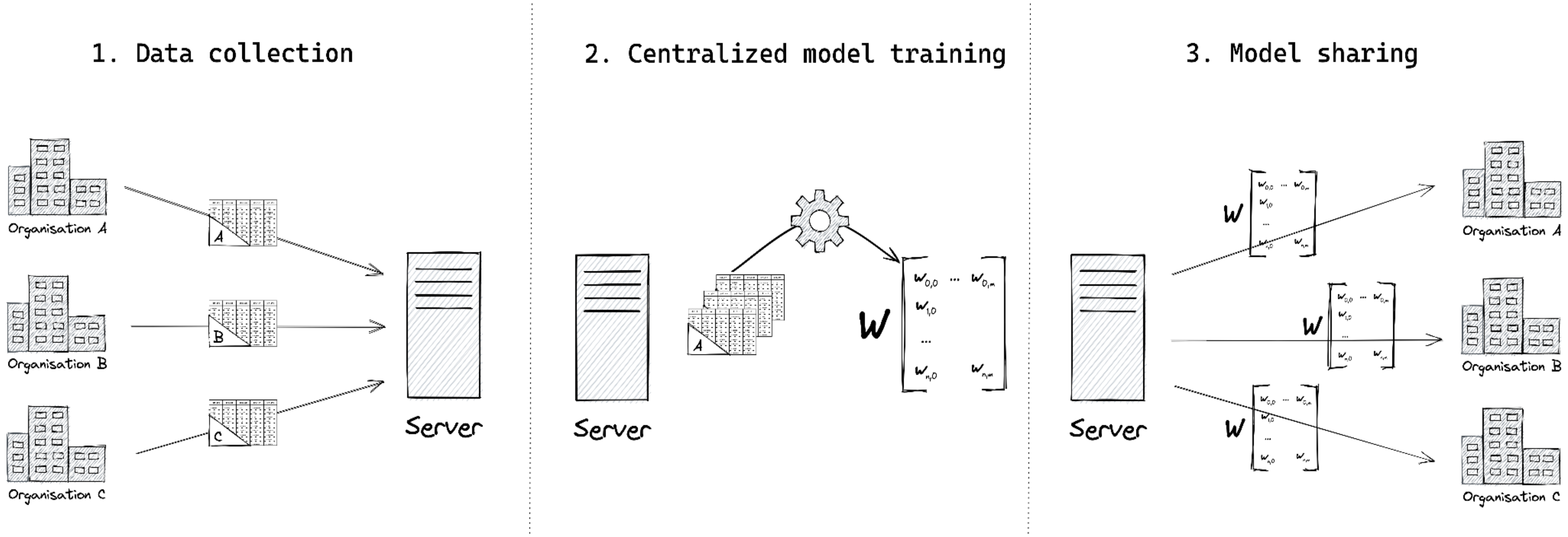
How to share experience in intrusion detection?



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

Collaborative Intrusion Detection

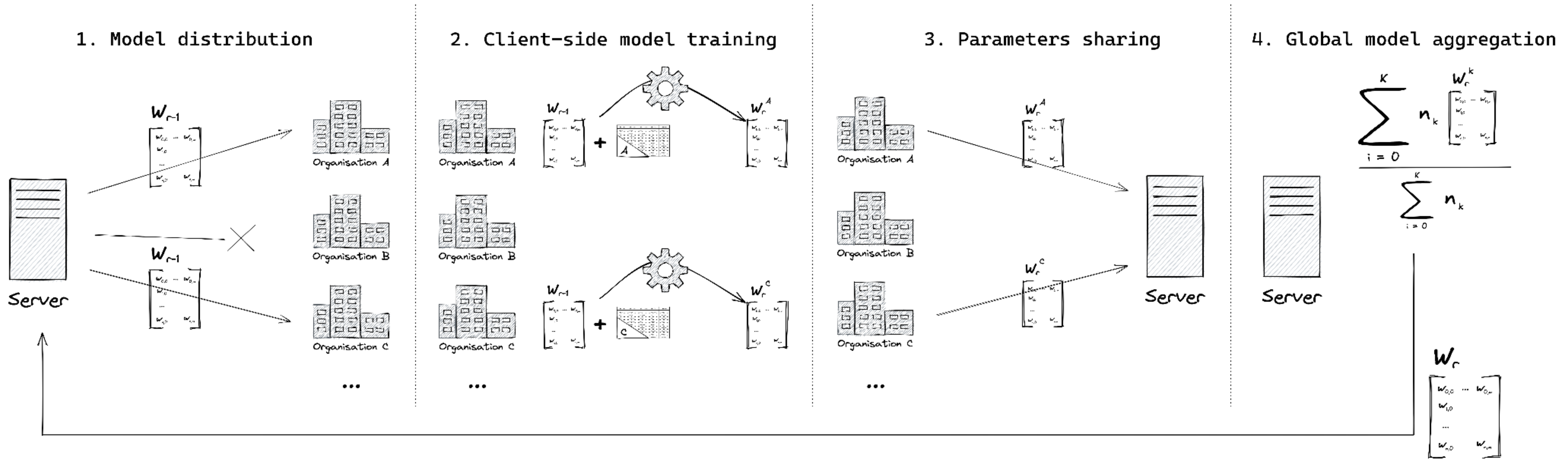
- **Objective**
  - Consolidate normal behavior modeling by sharing knowledge with other participants
- **Challenges**
  - Security & Privacy – *e.g.* revealing internals, poisoning, trust [1]
  - Availability – *e.g.* single point of failure in centralized systems [2]
  - Resources – *e.g.* high bandwidth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

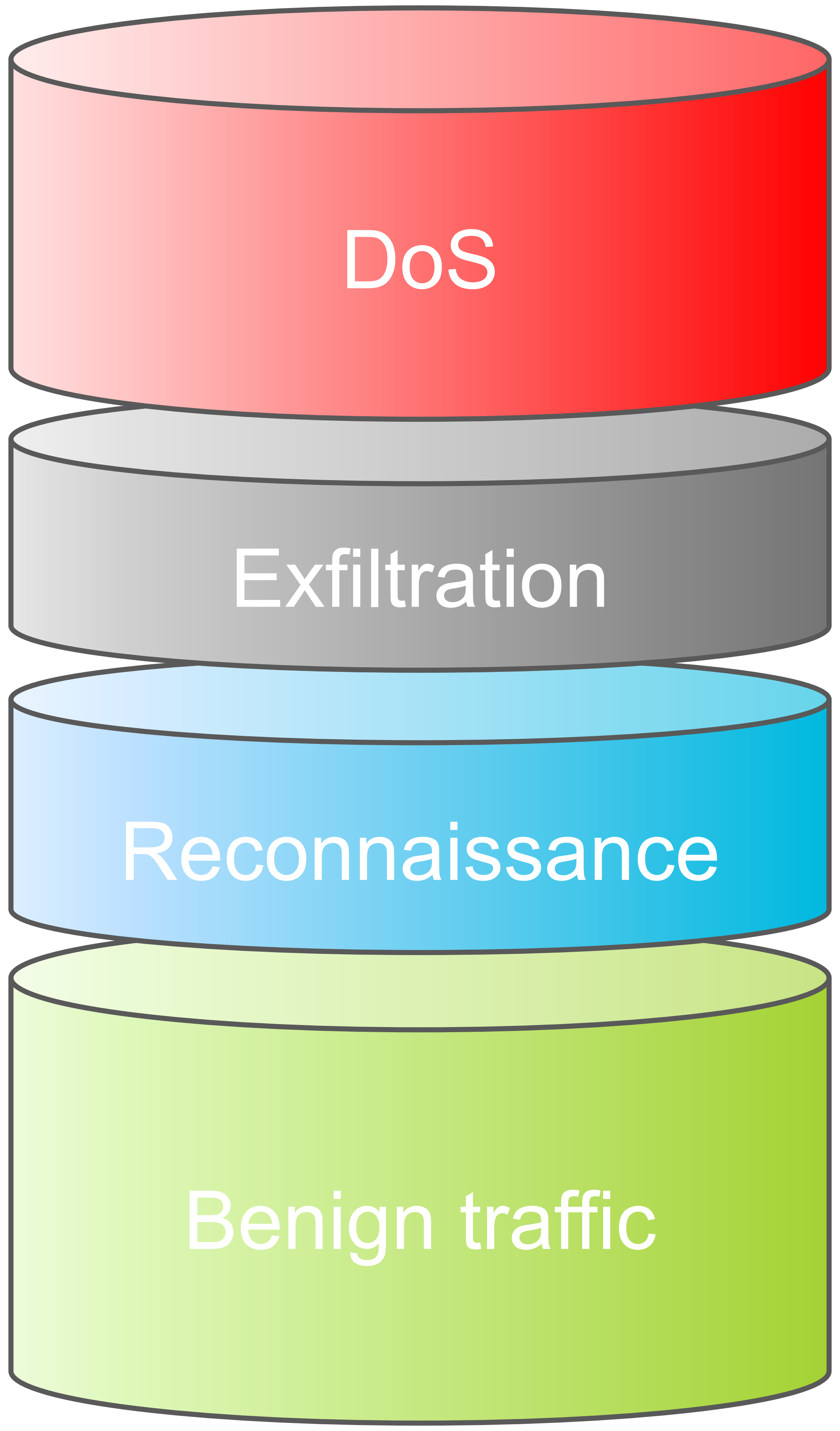
Federated Learning as a Collaborative Learning System

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

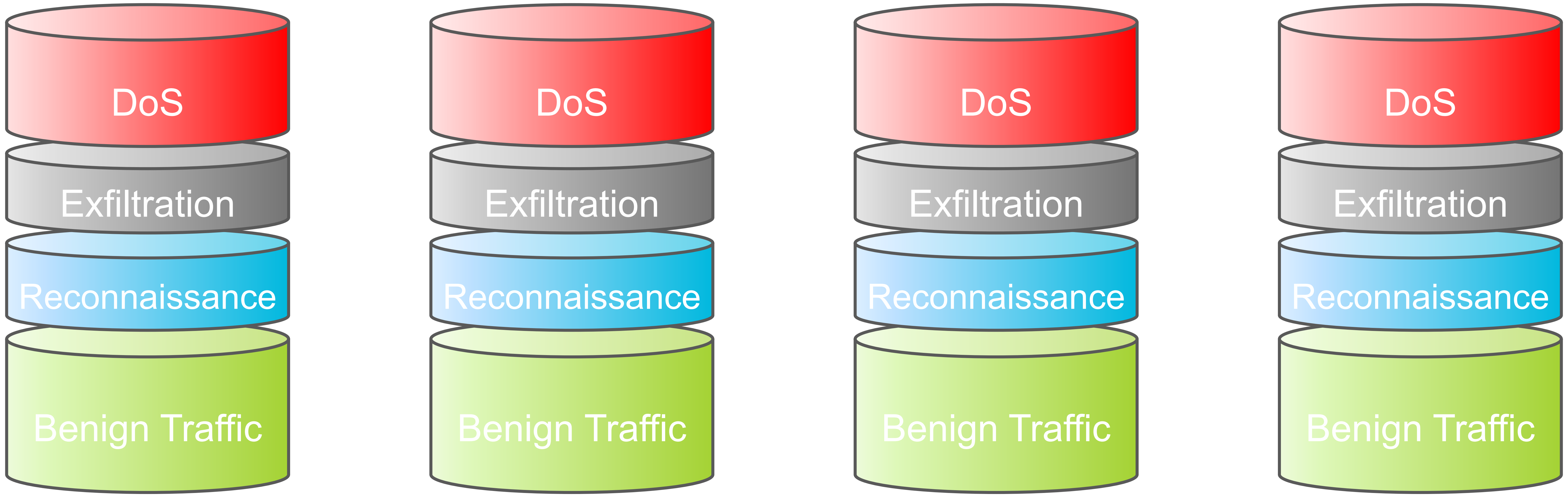


[4] L. Lavaur, et al., "The Evolution of Federated Learning-Based Intrusion Detection and Mitigation: A Survey", IEEE Transactions on Network and Service Management, 2022

- **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

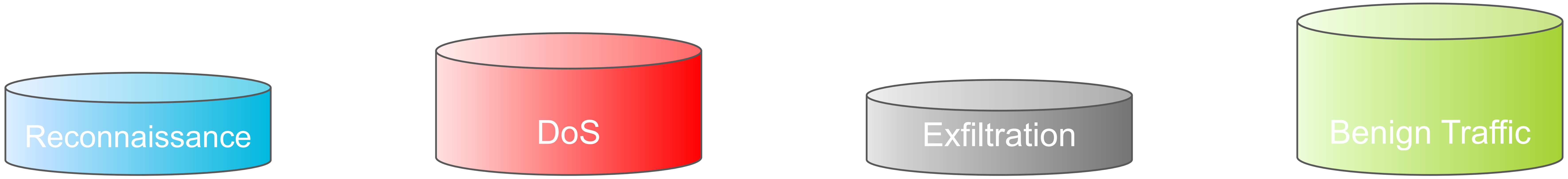


- **Homogeneous distribution of the dataset over 4 sites**
  - IID data (Independently and Identically Distributed)
  - No overlap in samples (disjoint data)



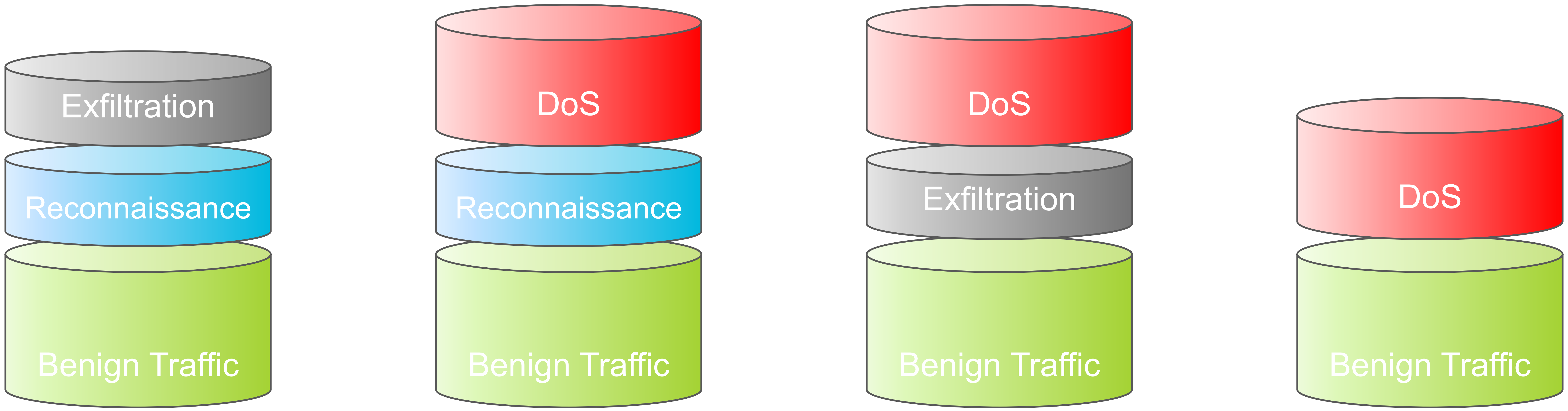
- **Differentiated distribution (NIID) of the dataset on 4 sites**
  - The data from the 4 sites do not contain the same attack classes

- **Pathological NIID [8]**
  - Only 1 class per client
  - Only 1 client per class
  - Not realistic in IDS context

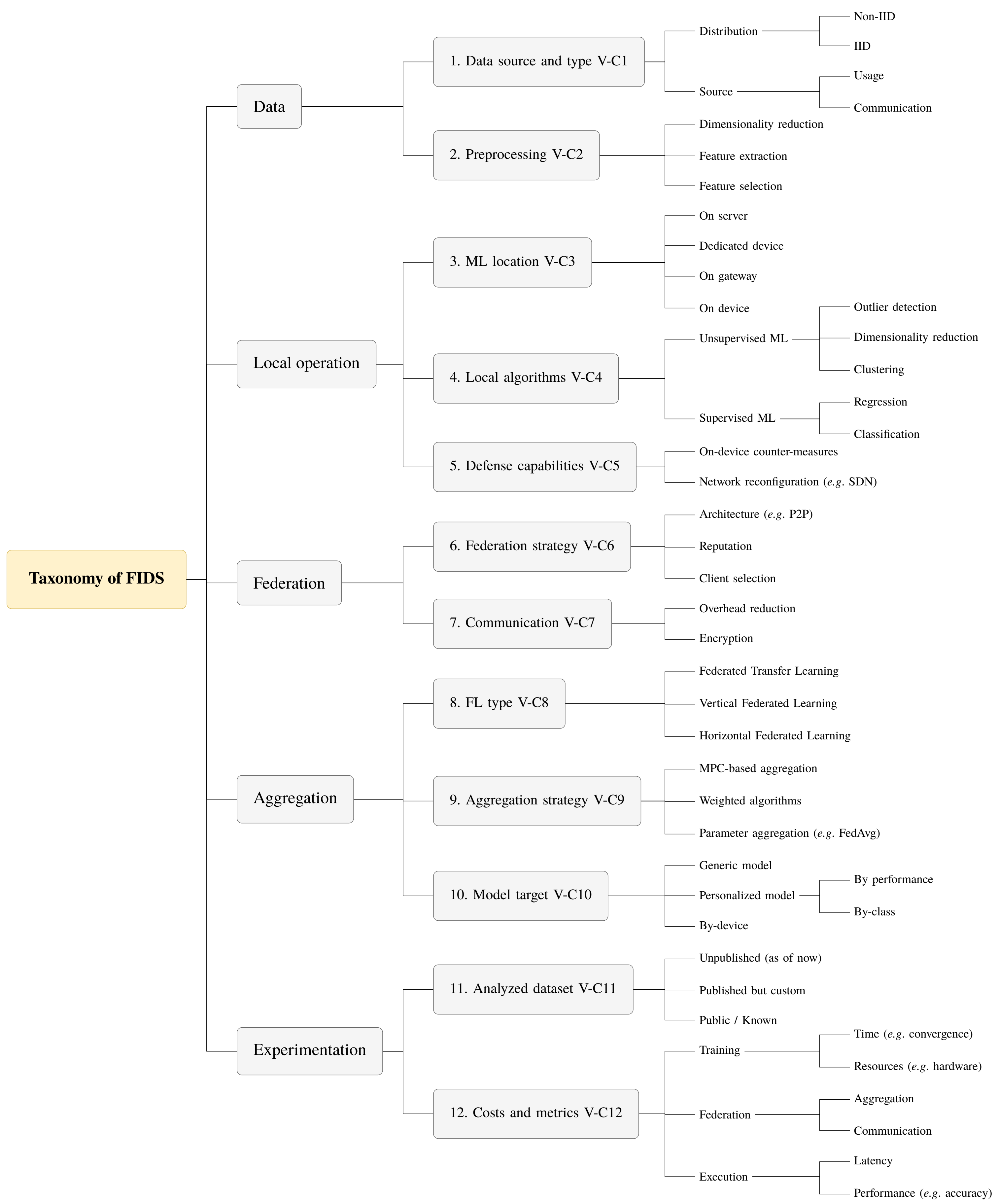


REALISTIC CASE: FEDERATED LEARNING ON HETEROGENOUS DATA

- **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



- **« 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

http://bit.ly/FLxSecu-part2

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

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

HOW TO SECURE THE FEDERATED LEARNING IN NETWORK MONITORING?

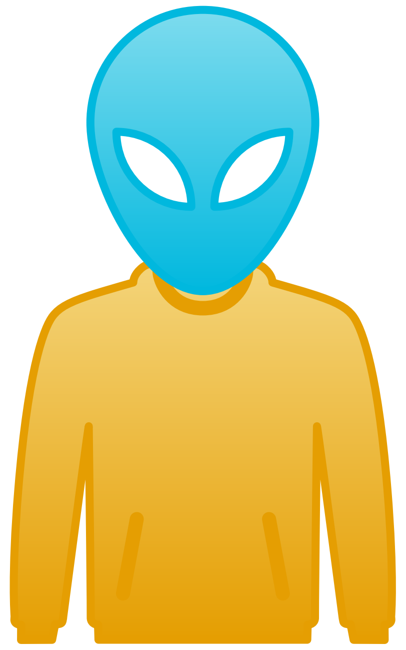
IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

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

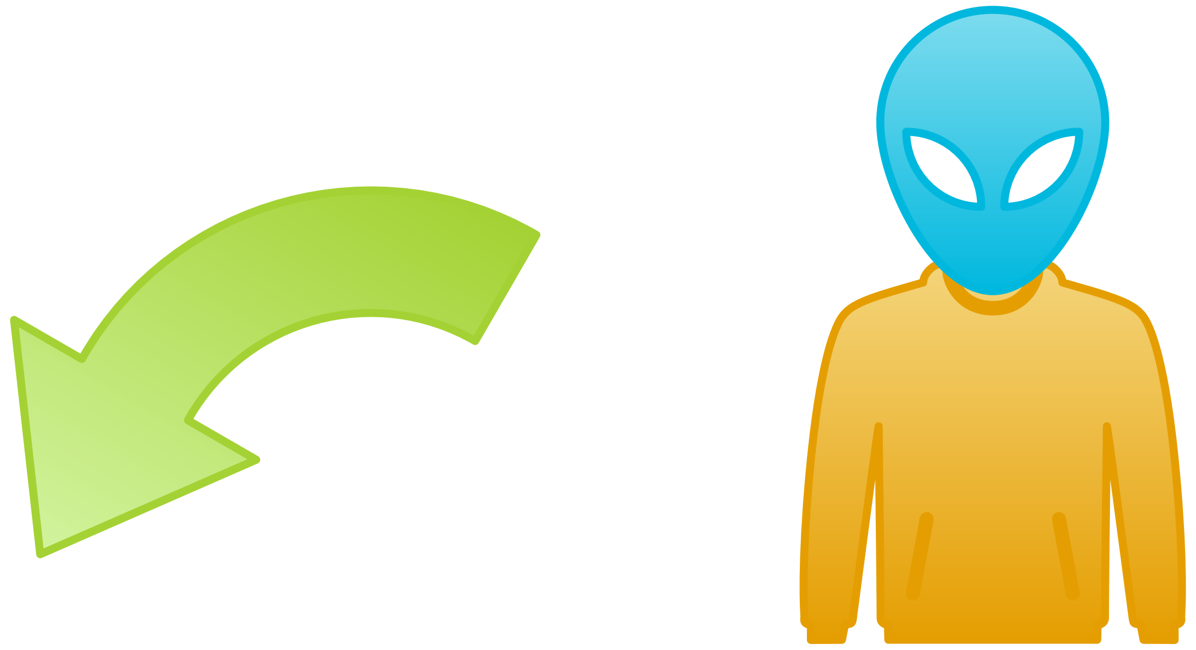
HOW TO SECURE THE FEDERATED LEARNING IN NETWORK MONITORING?

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

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



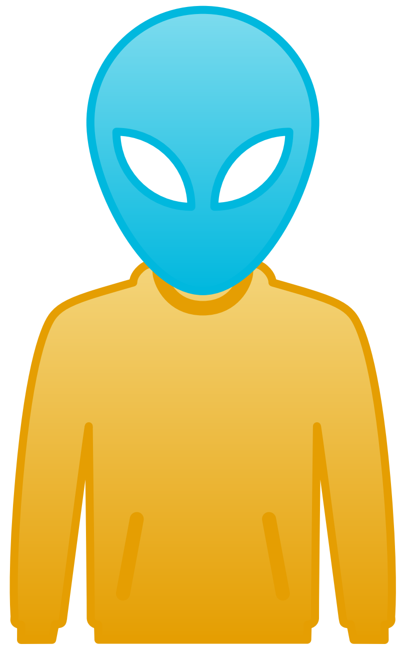
Adversarial attacks in federated learning



Adversarial attacks in federated learning

Attacks to the federated model

- Aim at modifying its behaviour



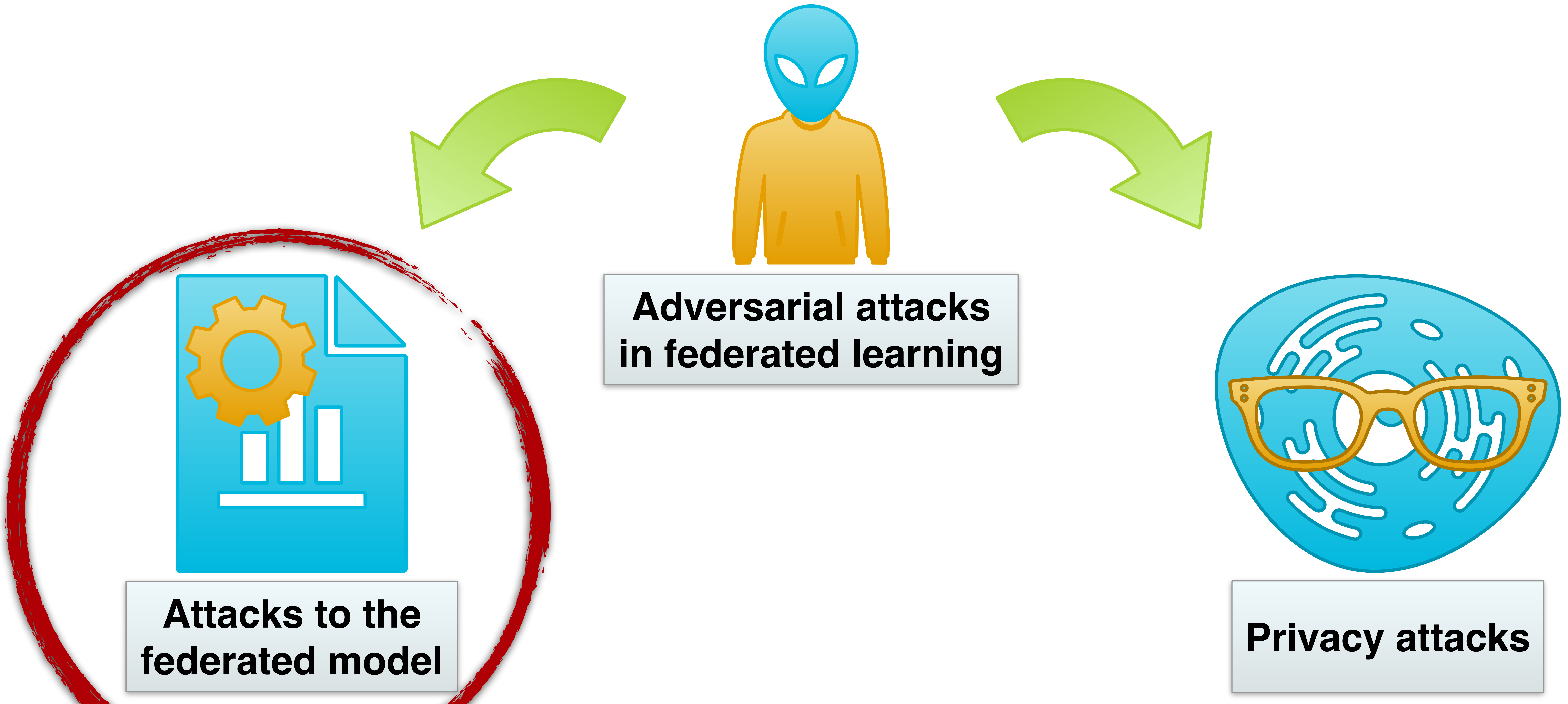
Adversarial attacks in federated learning

Attacks to the federated model

- Aim at modifying its behaviour

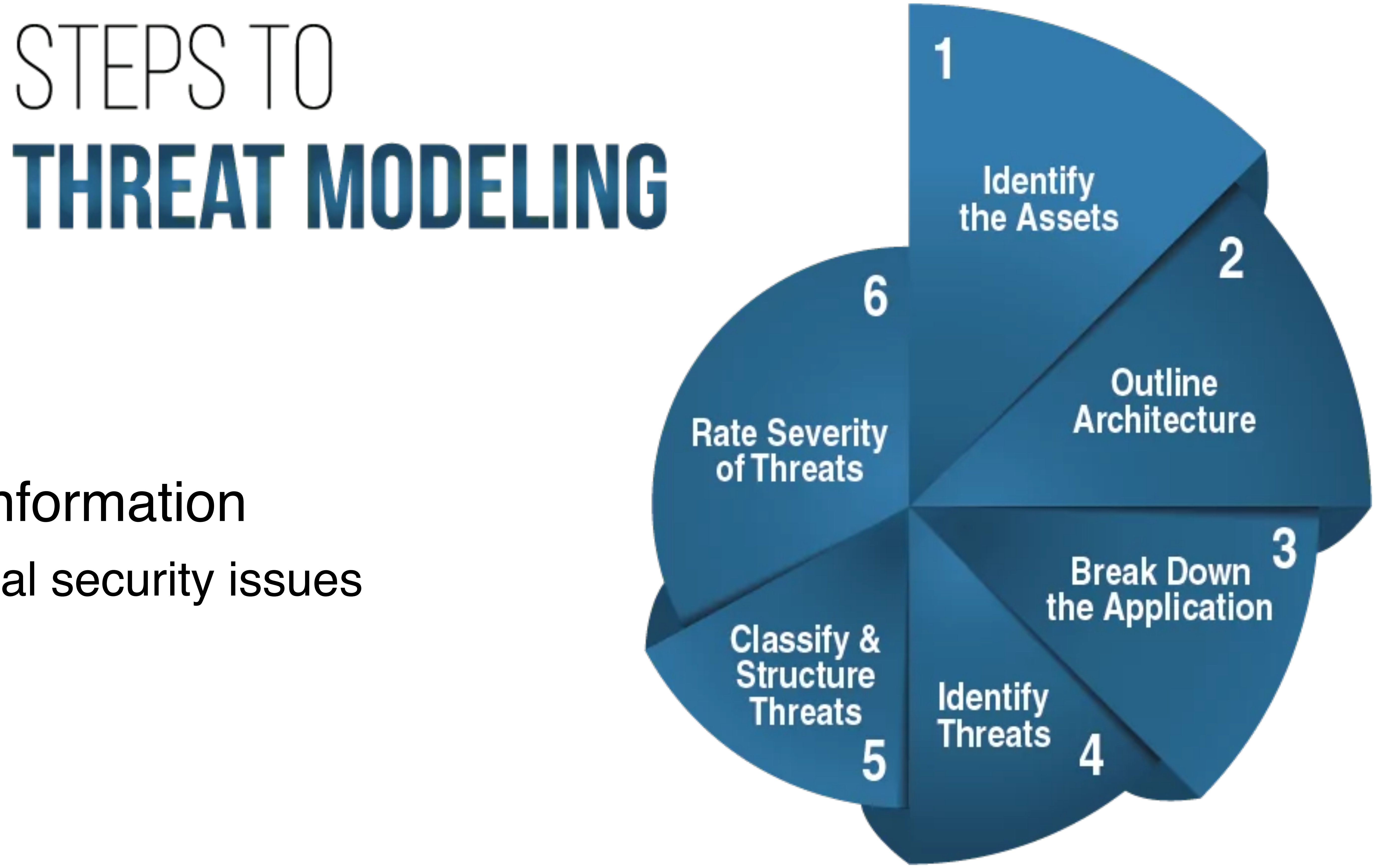
Privacy attacks

- Aim at inferring sensitive information from learning



- Aim at modifying its behaviour

- Aim at inferring sensitive information from learning



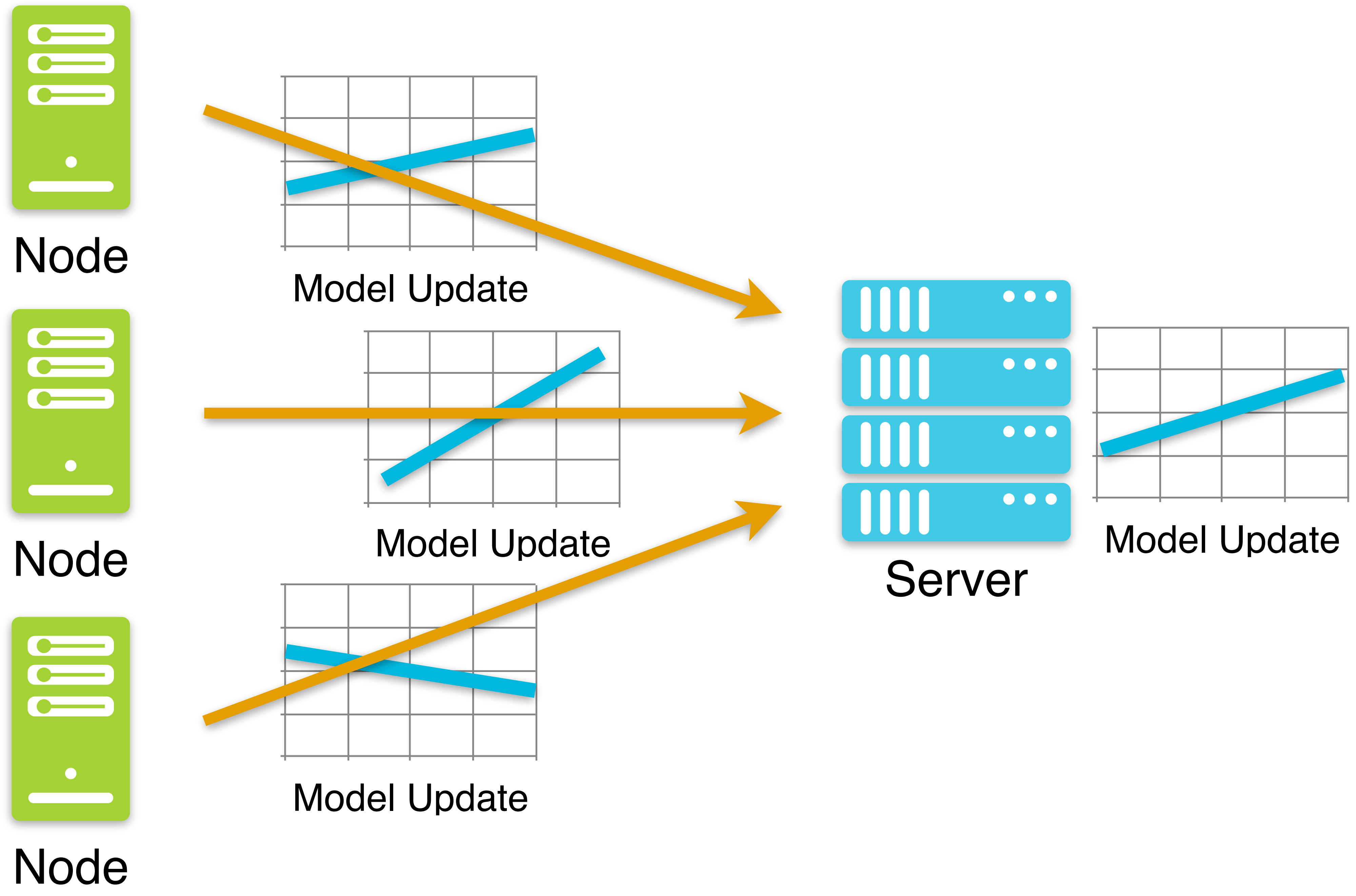
- **Threat model**
  - Structured representation of information
    - Help to identify and define potential security issues
  - Defined in terms of
    - Information available
    - Scope of action of the attacker

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

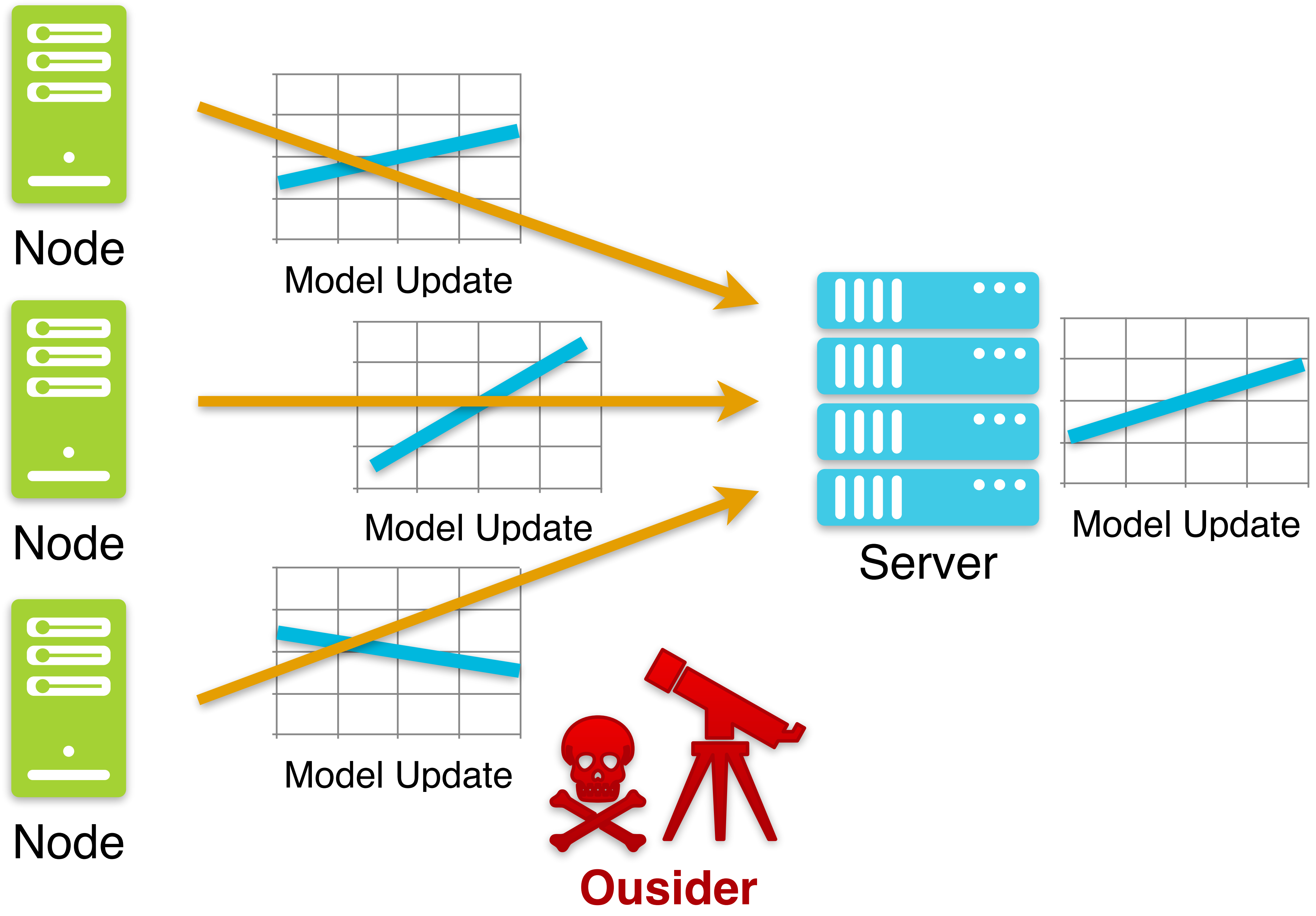
THREAT MODEL: INSIDER *VS.* OUTSIDER

- **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
  - Aimed at **modifying the behaviour** of the model or **inferring valuable information** from other clients

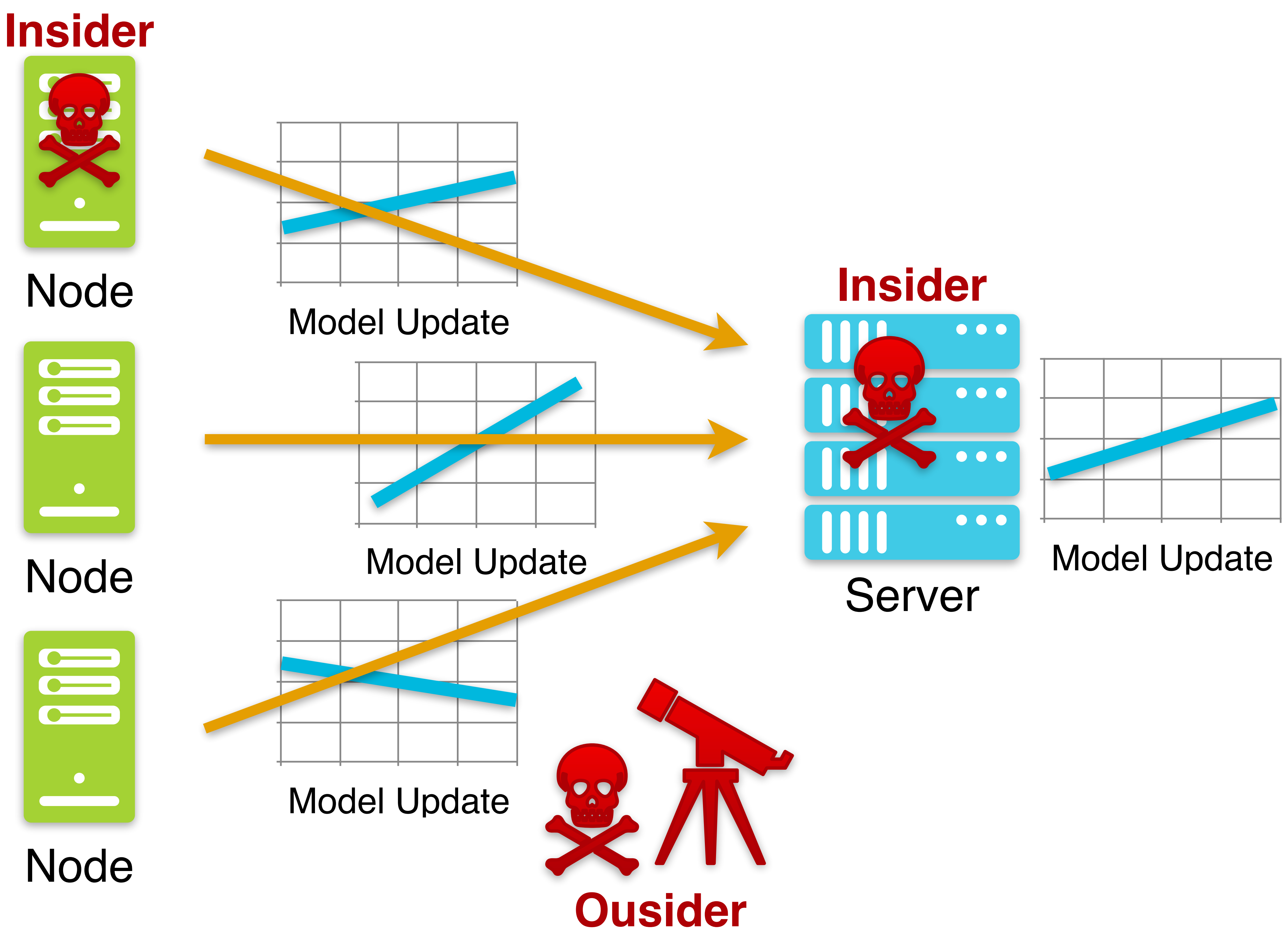
- **Ousider**
  - Mainly focus on sniffing information of the communication channels between the involved agents
  - Aimed at **inferring information** about the data or the resulting learning model
- **Insider**
  - **More harmful**
  - Attack is carried out by one (or coalition) of the participants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



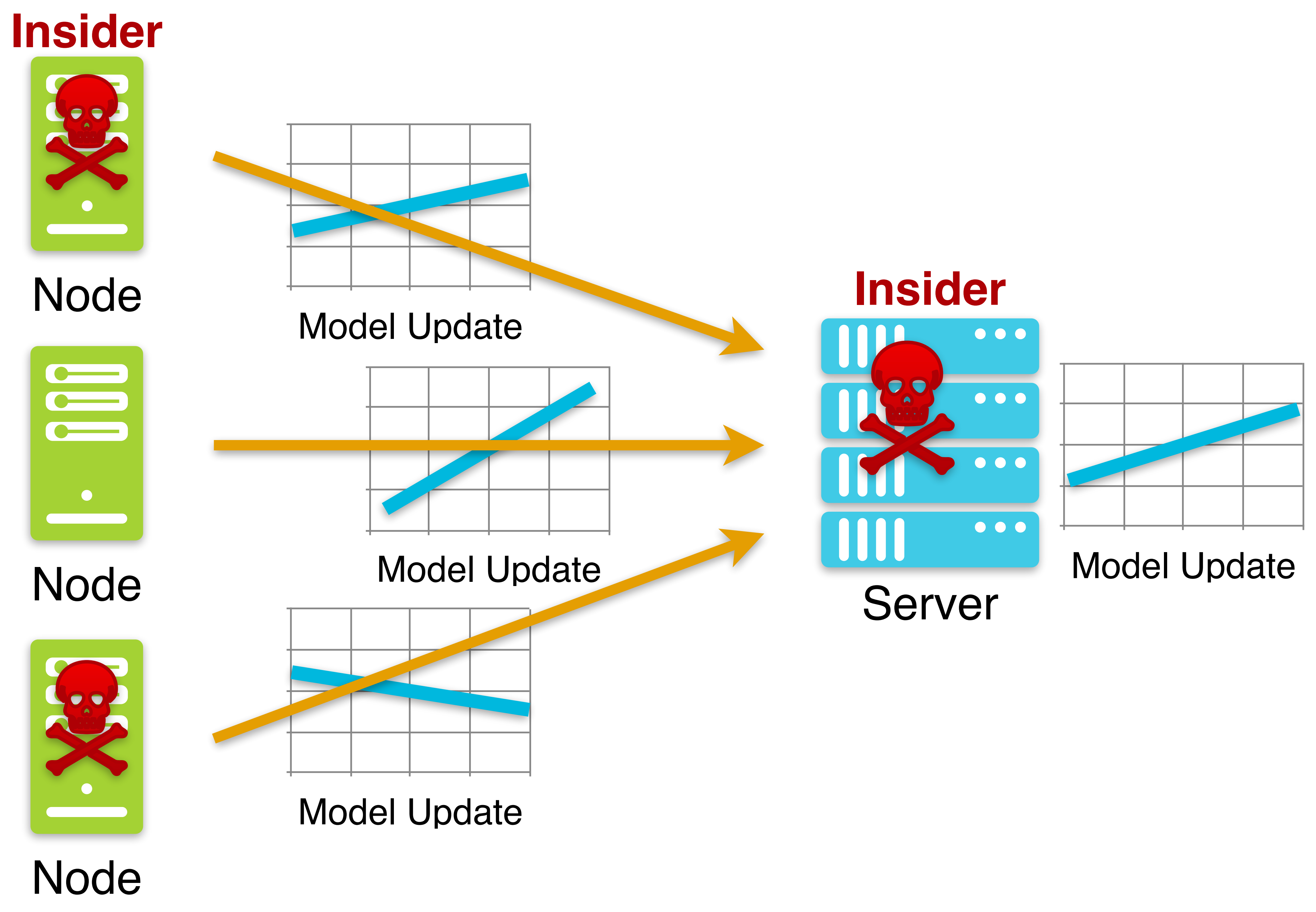
- **Ousider**
  - Mainly focus on sniffing information of the communication channels between the involved agents
  - Aimed at **inferring information** about the data or the resulting learning model
- **Insider**
  - **More harmful**
  - Attack is carried out by one (or coalition) of the participants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



- **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
  - Aimed at **modifying the behaviour** of the model or **inferring valuable information** from other clients

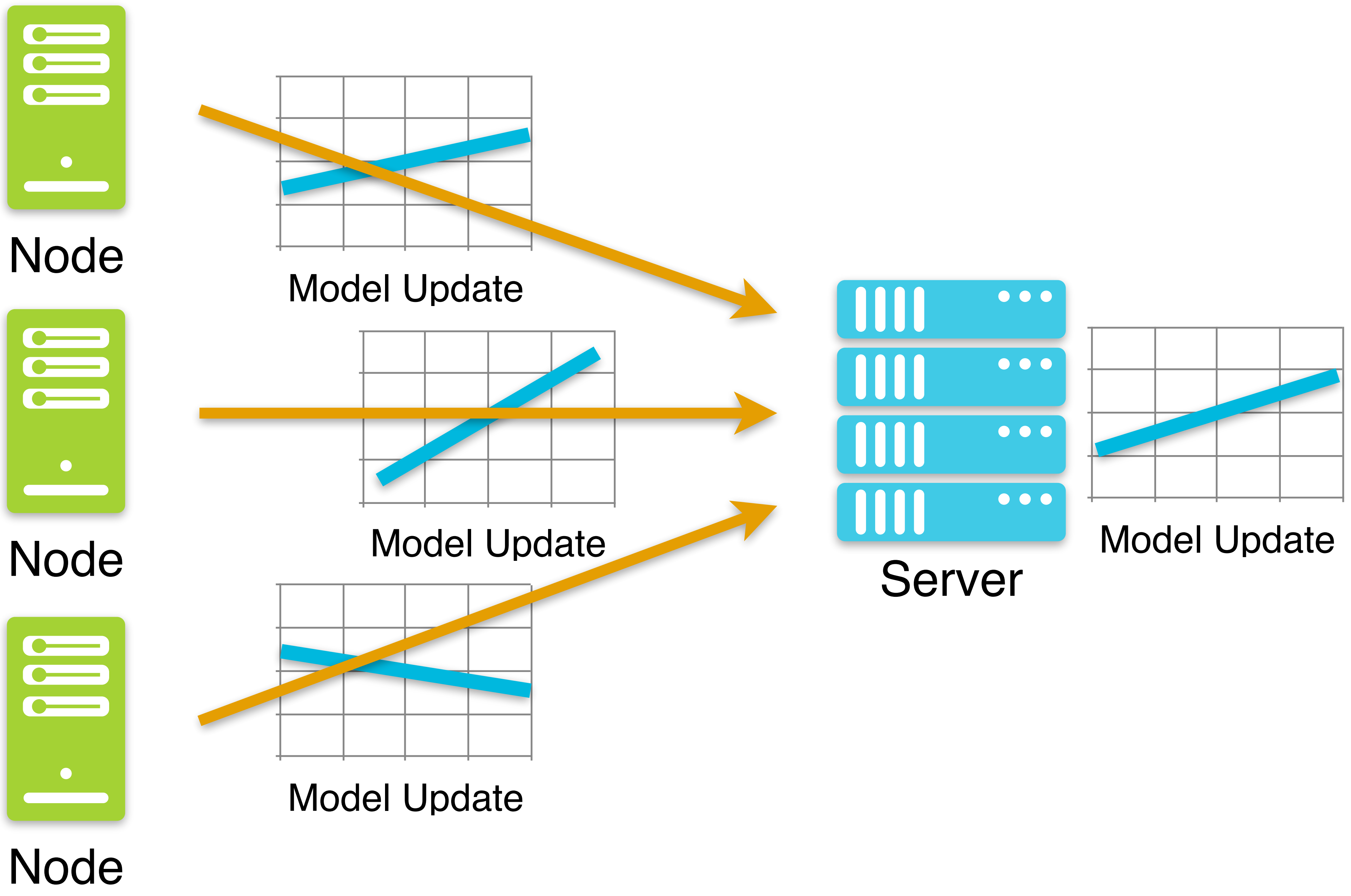


- **Byzantine attacks**
  - Consist in sending arbitrary updates to the server
  - Aim to compromise the performance of the global learning model.
- **Sybil attacks**
  - Consist of collaborative attacks
    - By several attackers joining together
    - By simulating fictitious clients in order to be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



ADVERSARIAL ATTACKS IN FEDERATED LEARNING

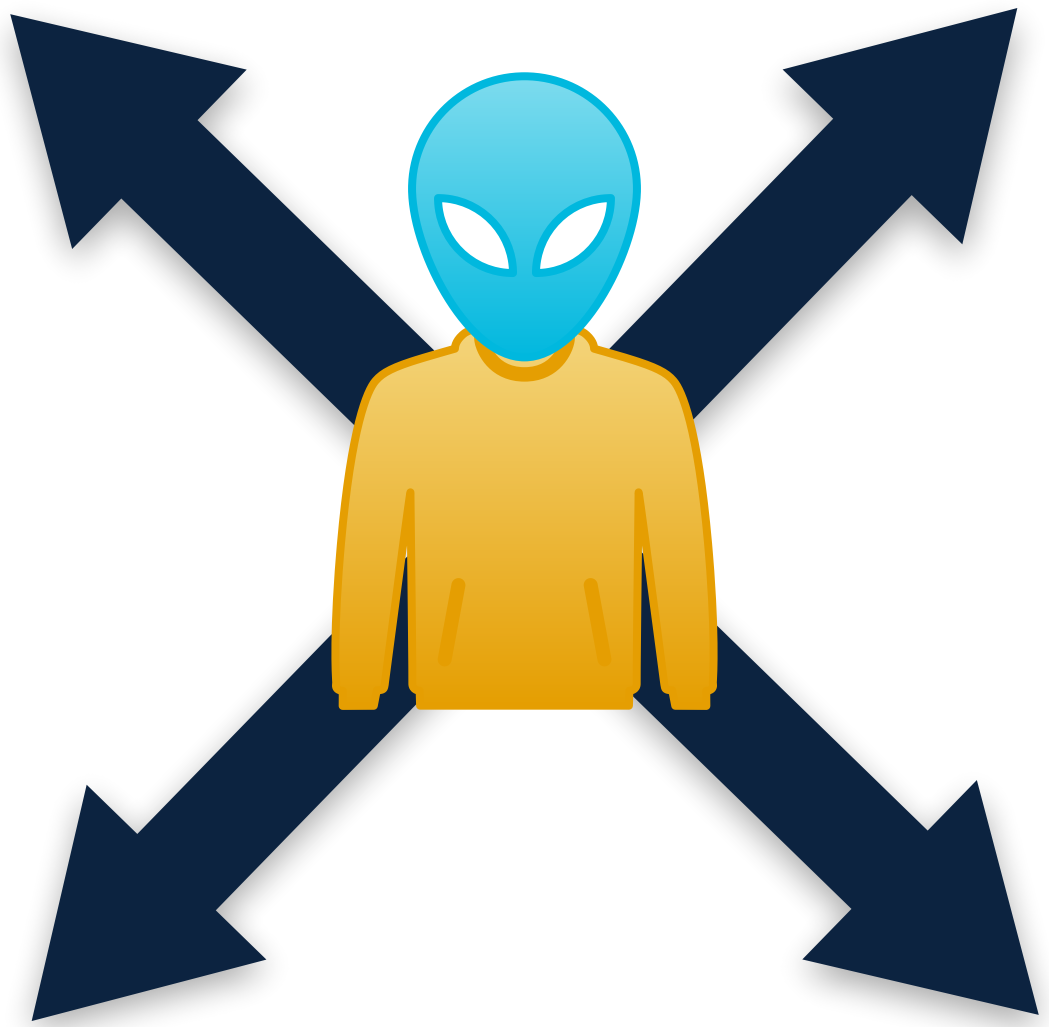
IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

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

UMR IRISA

- **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]

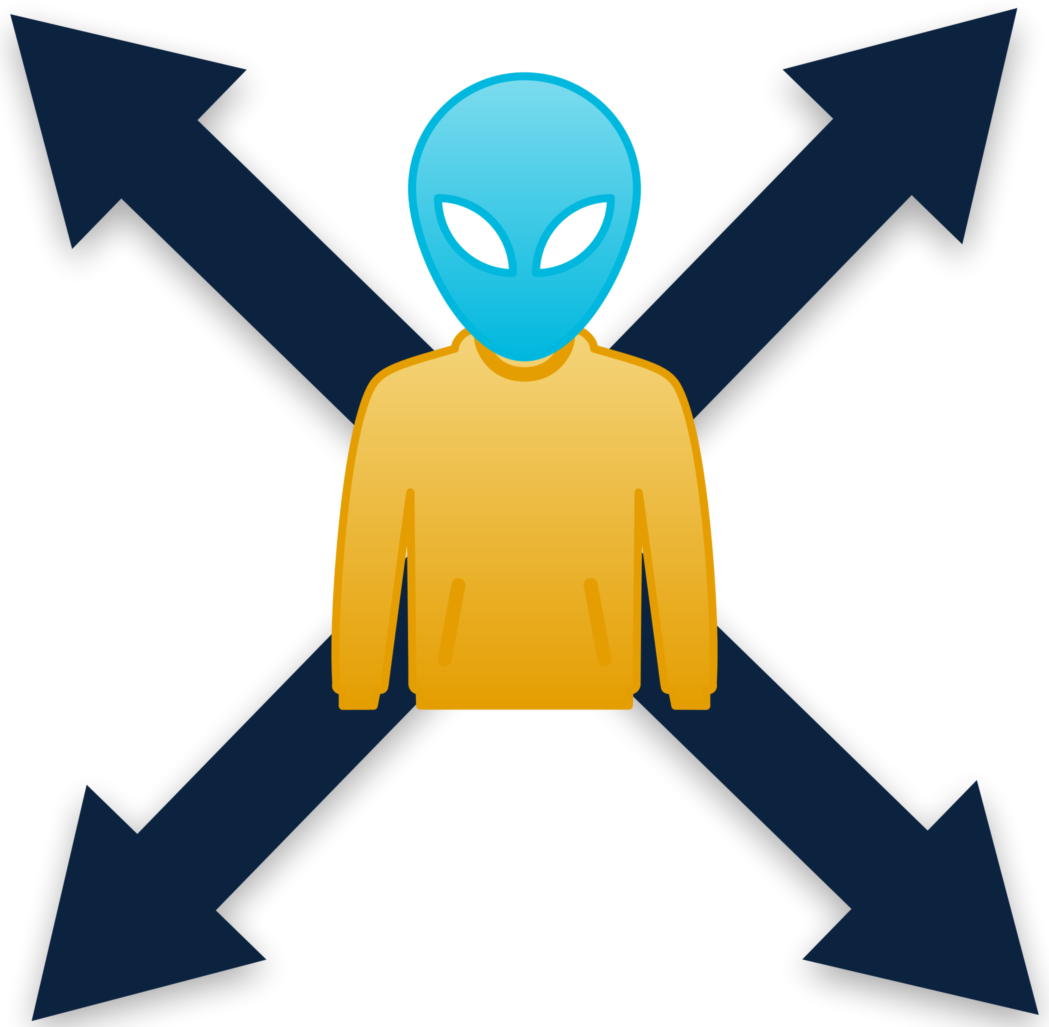


4 TAXONOMIES OF ATTACKS [2]

Attack moment

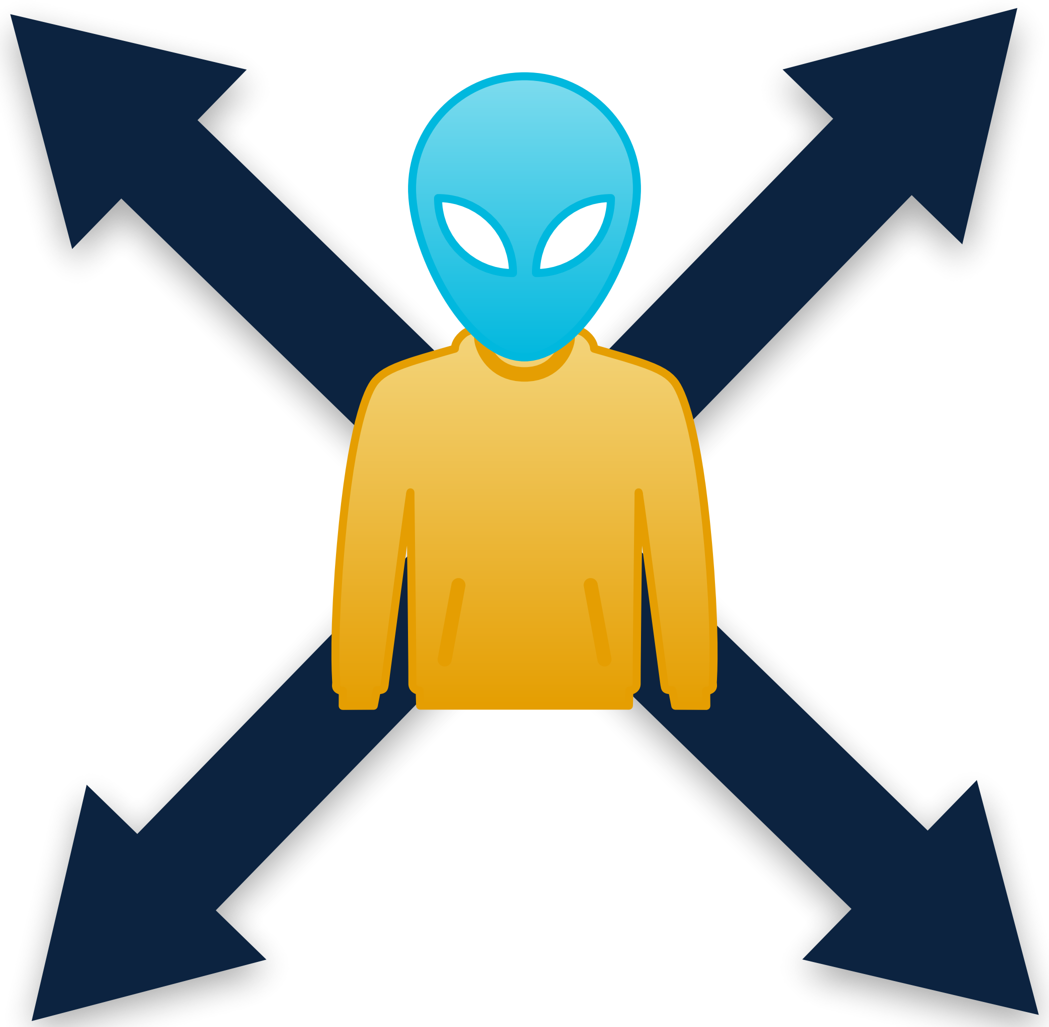
Training time attacks

Inference time attacks



Attack moment

- Training time attacks
- Inference time attacks



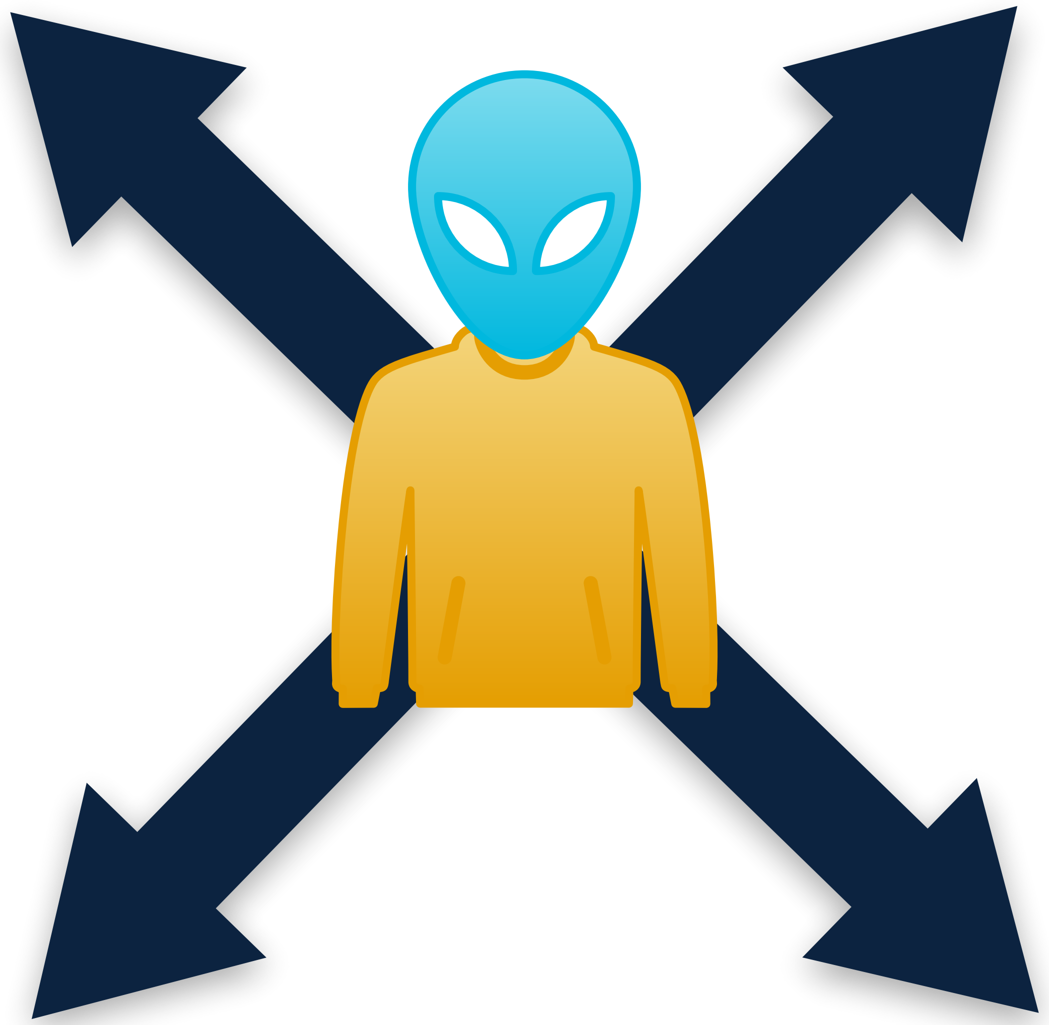
Objective

- Untargeted attacks
- Targeted/backdoor attacks

4 TAXONOMIES OF ATTACKS [2]

Attack moment
- Training time attacks
- Inference time attacks

Objective
- Untargeted attacks
- Targeted/backdoor attacks

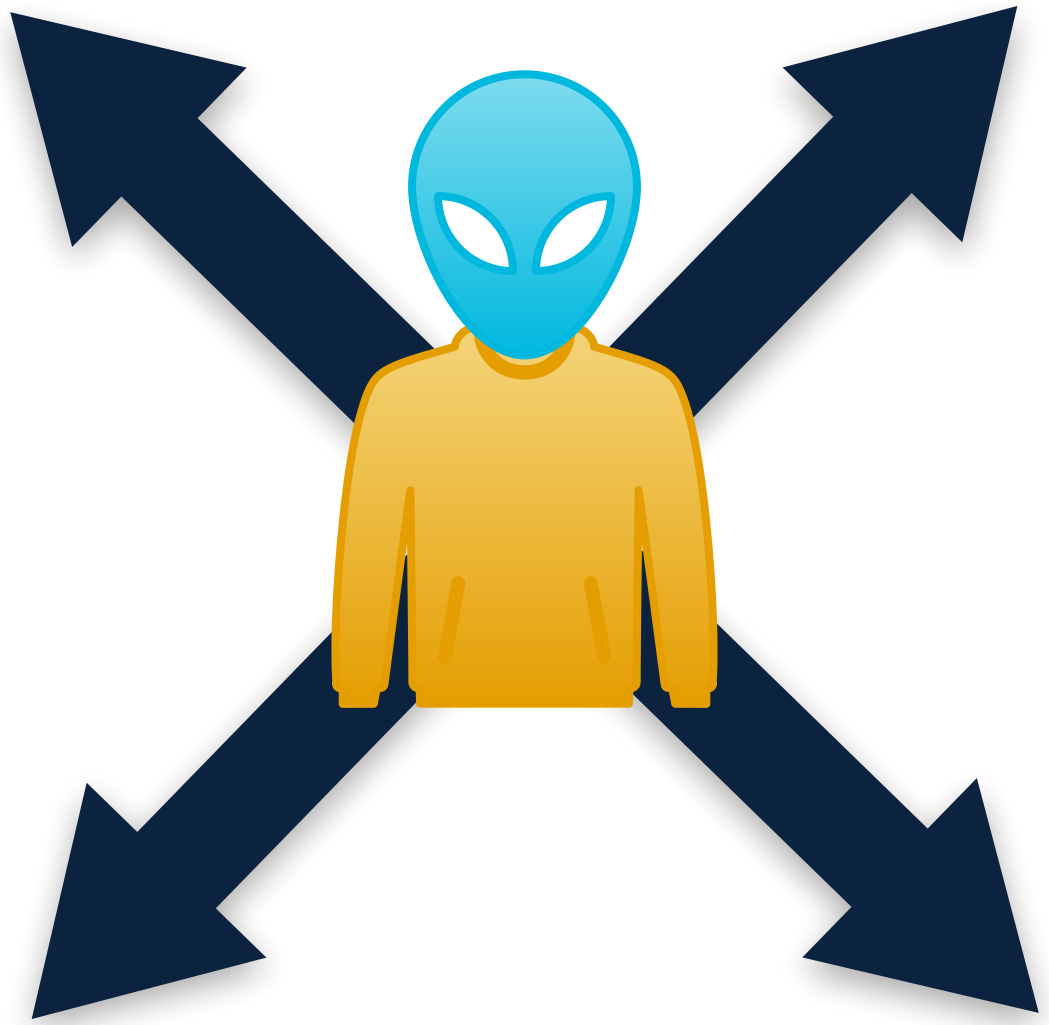


Poisoned part
- Data-poisoning attacks
- Model-poisoning attacks

4 TAXONOMIES OF ATTACKS [2]

Attack moment
- Training time attacks
- Inference time attacks

Objective
- Untargeted attacks
- Targeted/backdoor attacks



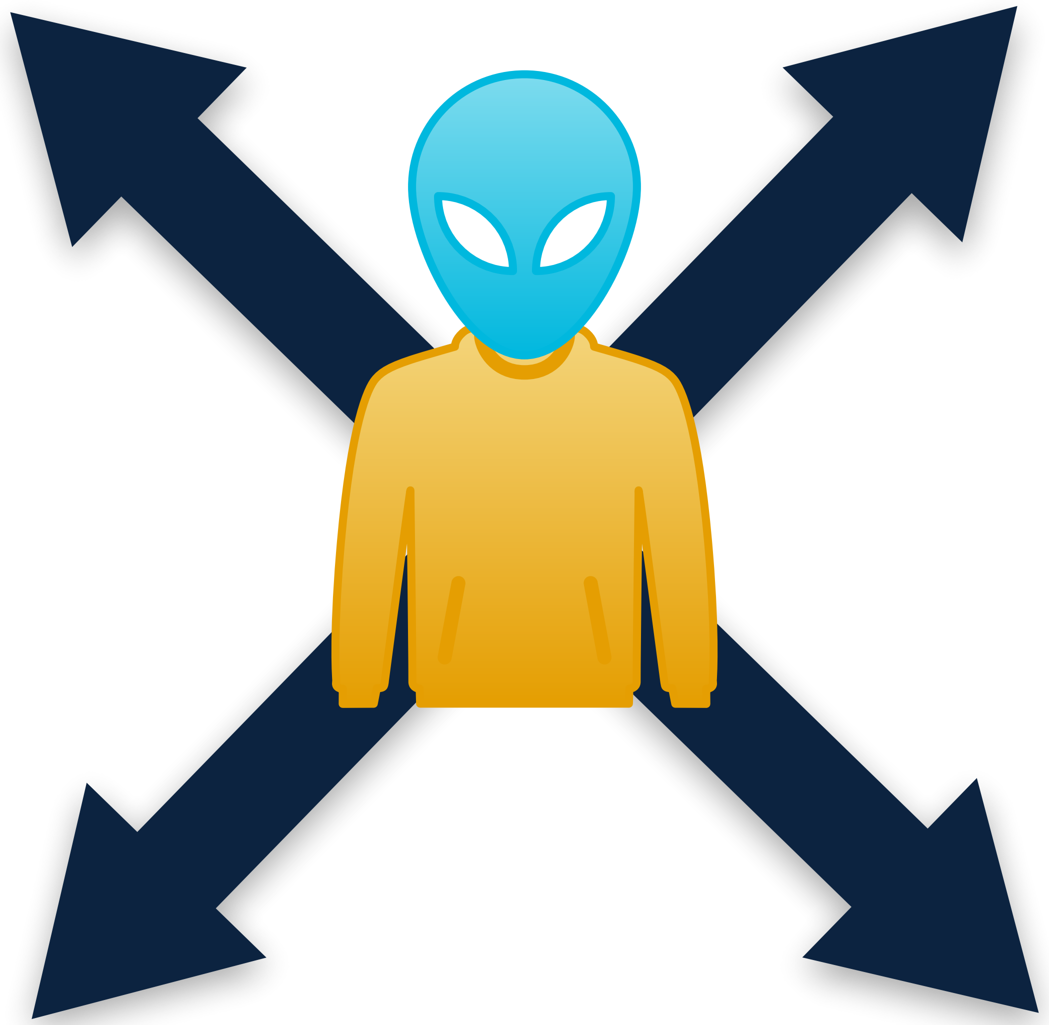
Poisoned part
- Data-poisoning attacks
- Model-poisoning attacks

Frequency
- One-shot attack
- Multiple or adaptive attack

4 TAXONOMIES OF ATTACKS [2]

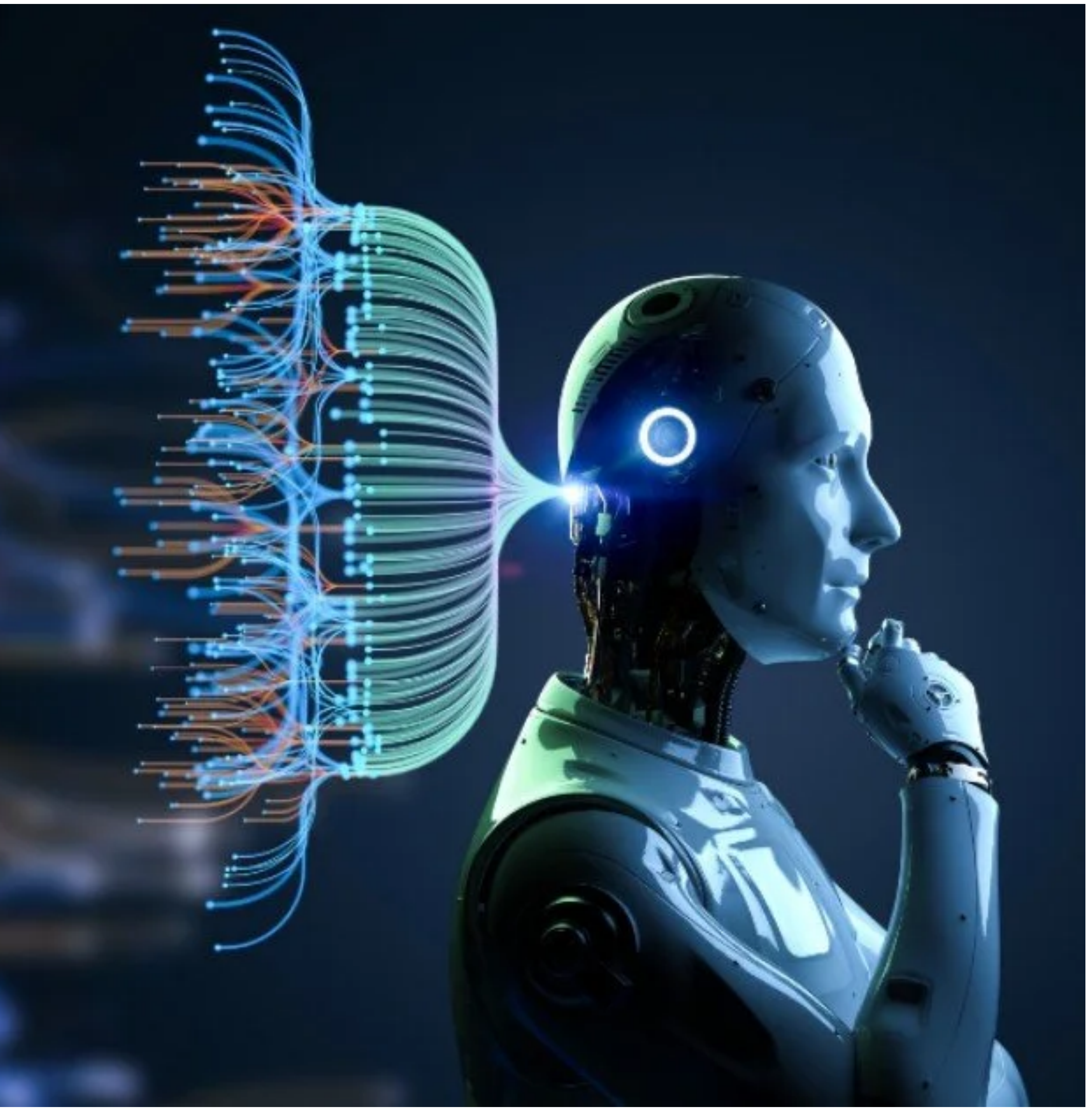
Attack moment
- Training time attacks
- Inference time attacks

Objective
- Untargeted attacks
- Targeted/backdoor attacks



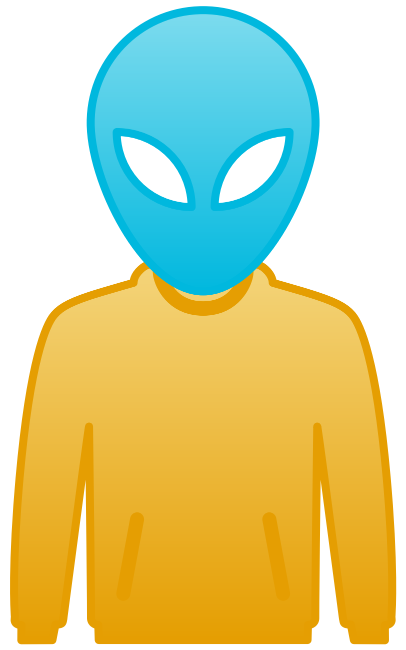
Poisoned part
- Data-poisoning attacks
- Model-poisoning attacks

Frequency
- One-shot attack
- Multiple or adaptive attack



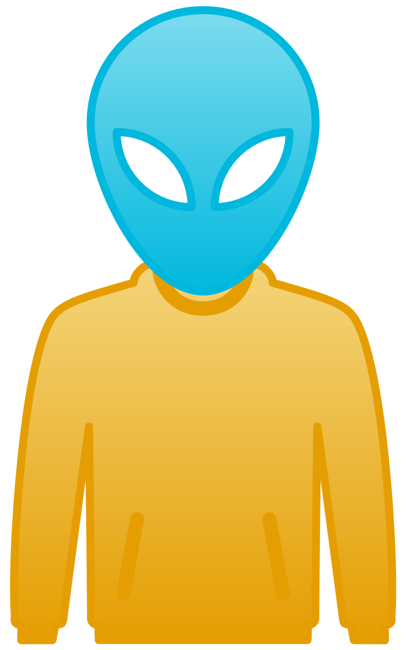
- **Inject small amount of malicious data into the benign traffic, which will not be detected as anomalous**
  - The model will not detect the backdoored traffic as malicious
  - Security gateway uses this data to train the local model
  - Local model will be sent to the aggregator, hence affecting the 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]



Objective
Untargeted attacks
Targeted/backdoor attacks

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

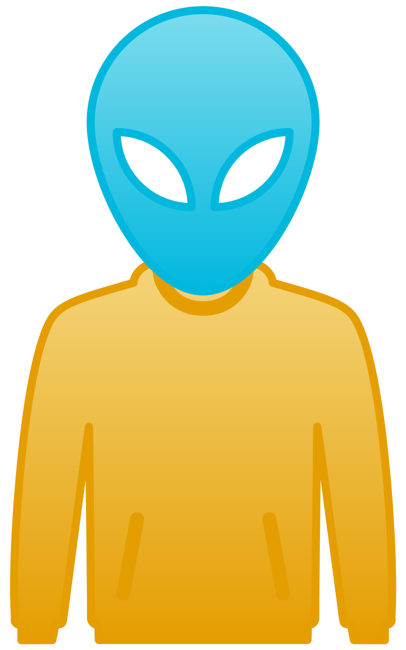


Objective

Untargeted attacks

Targeted/backdoor attacks

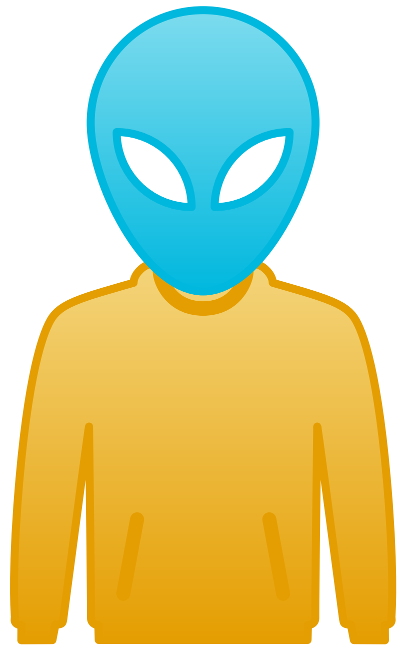
Input-instance-key strategies



Objective

- Untargeted attacks
- Targeted/backdoor attacks
  - **Input-instance-key strategies**
  - **Pattern-key strategies**

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

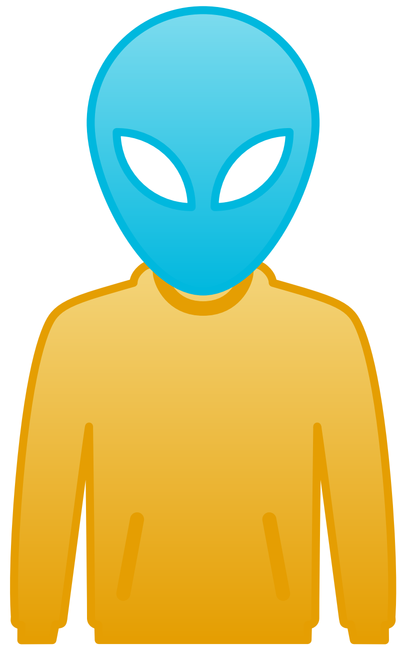


Objective

- Untargeted attacks
- Targeted/backdoor attacks
  - **Input-instance-key strategies**
  - **Pattern-key strategies**

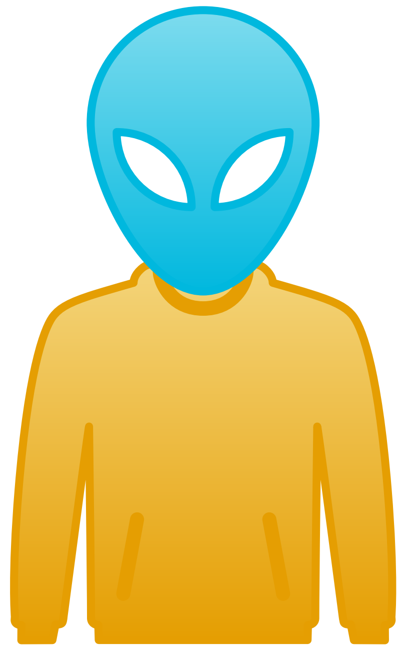
Design of the pattern

- Blended injection strategy
- Accessory injection strategy
- Blended accessory injection strategy



Objective

- Untargeted attacks
- Targeted/backdoor attacks
  - **Input-instance-key strategies**
  - **Pattern-key strategies**
    - **Design of the pattern**
      - Blended injection strategy
      - Accessory injection strategy
      - Blended accessory injection strategy
    - **Number of patterns**
      - Single pattern attack
      - Multi-backdoor attack (Sybil)



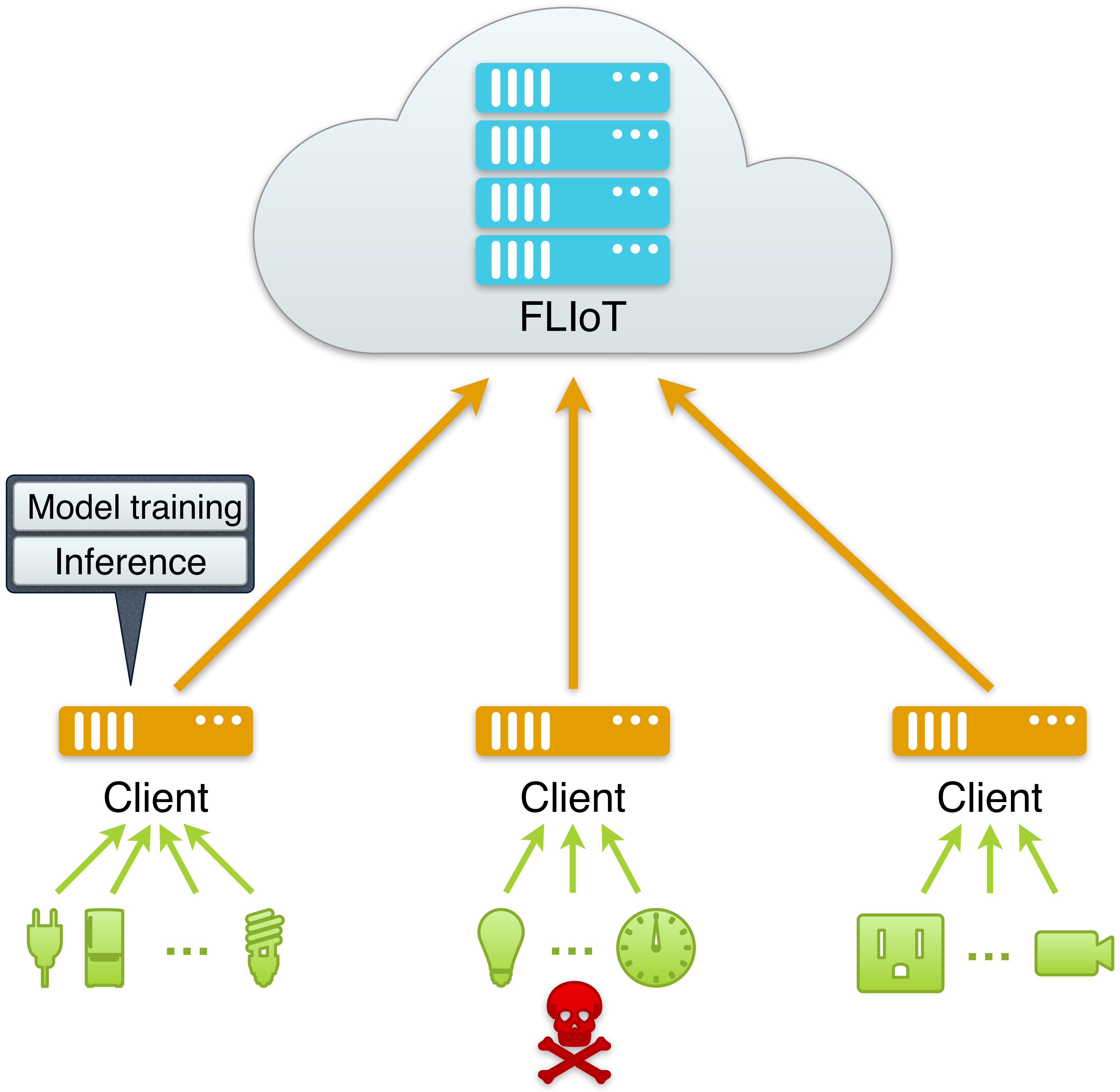
Objective
- Untargeted attacks
- Targeted/backdoor attacks
  - Input-instance-key strategies
  - Pattern-key strategies

Design of the pattern
- Blended injection strategy
- Accessory injection strategy
- Blended accessory injection strategy

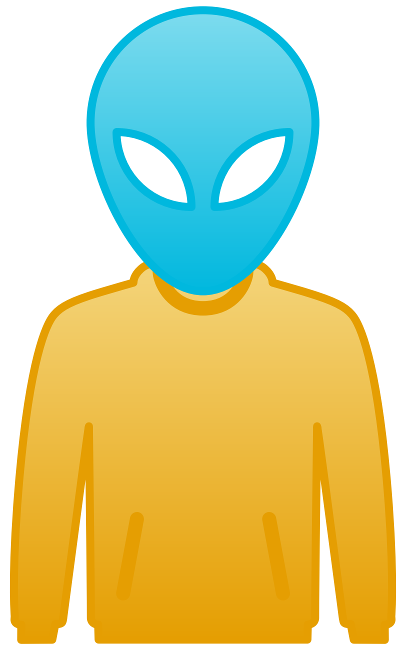
Number of patterns
- Single pattern attack
- Multi-backdoor attack (Sybil)

Variability over time
- Static attack
- Dynamic attack

- **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**



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

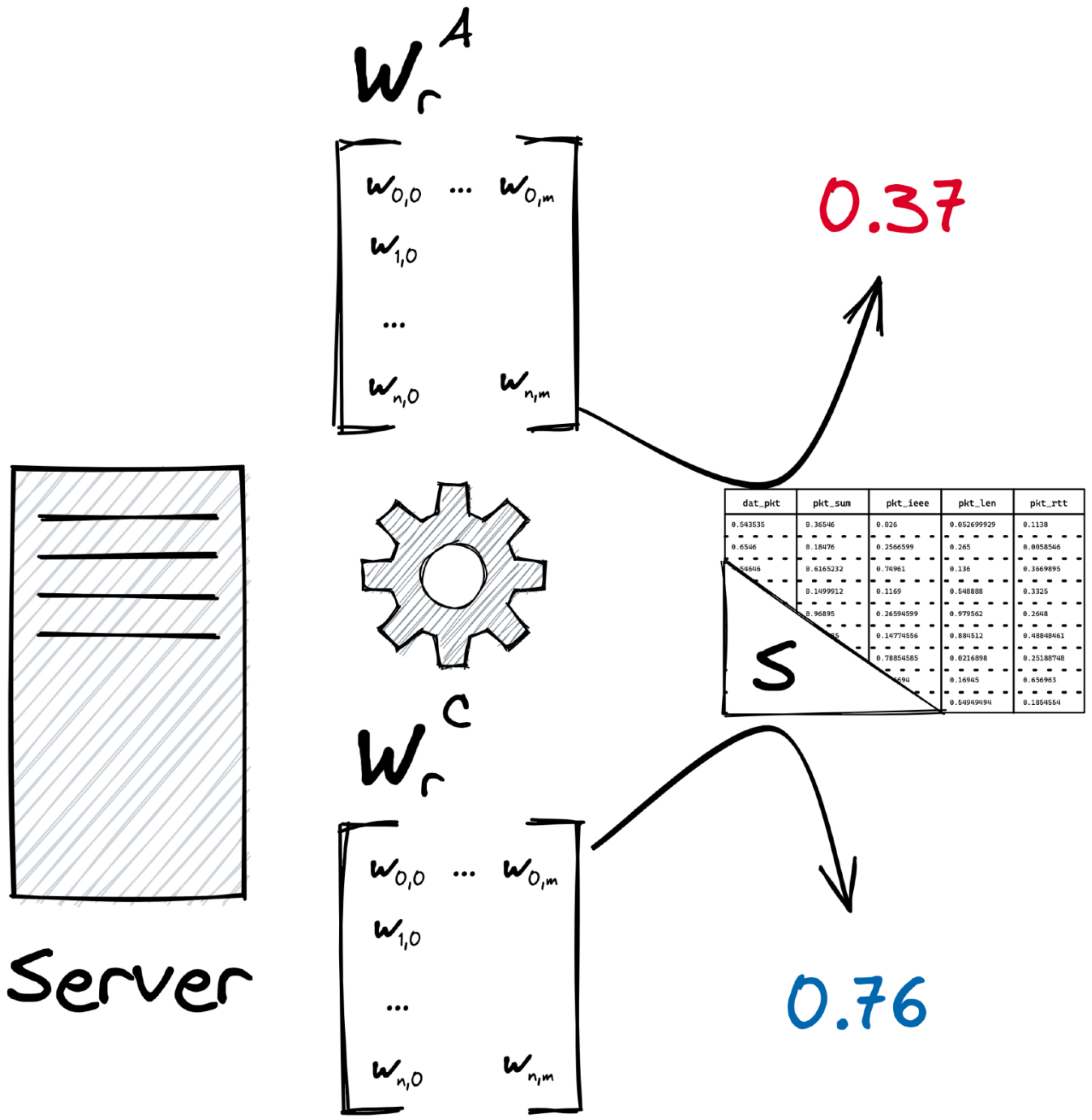
METHODS FOR FILTERING CONTRIBUTIONS IN FEDERATED LEARNING

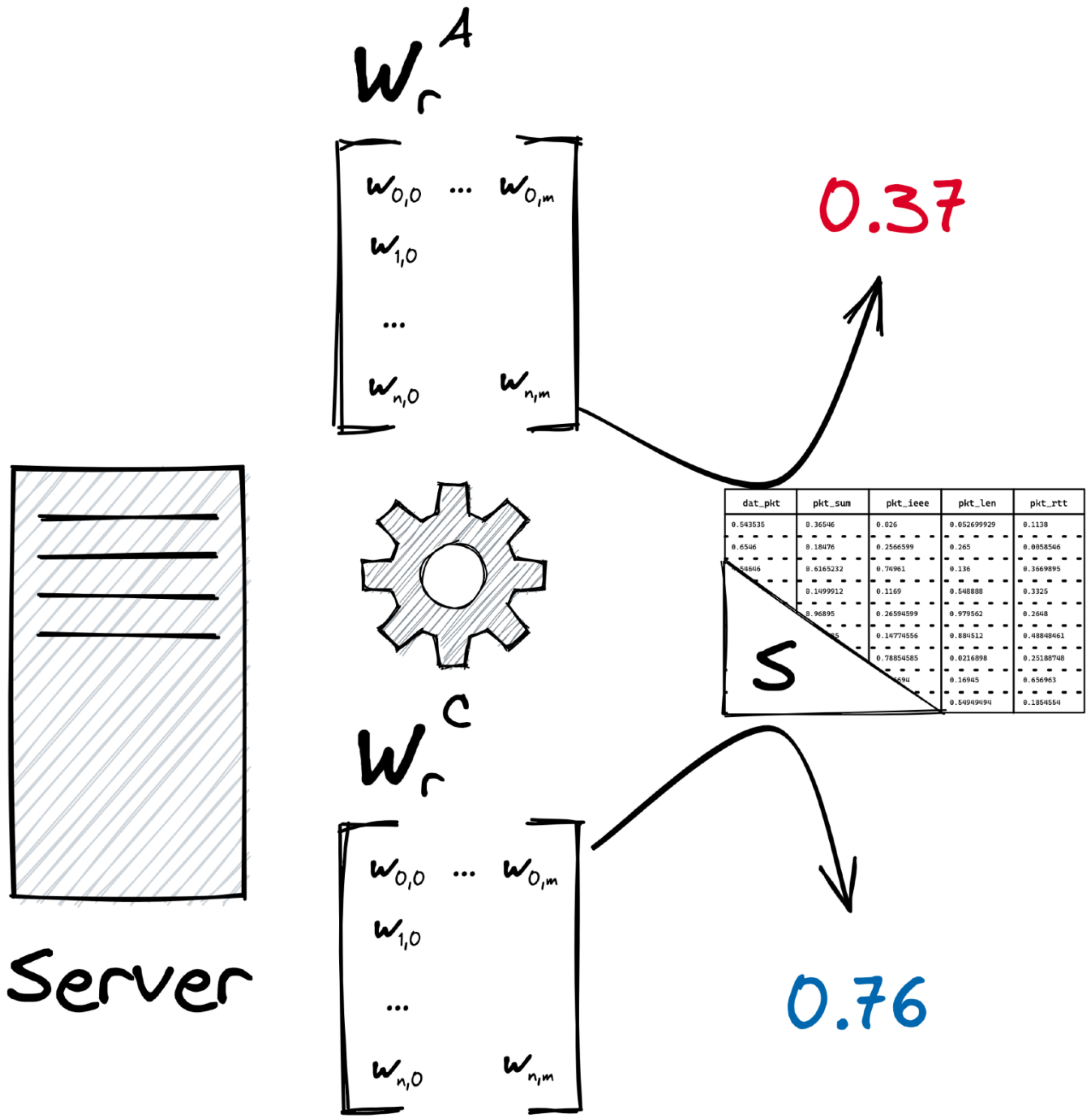
IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

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

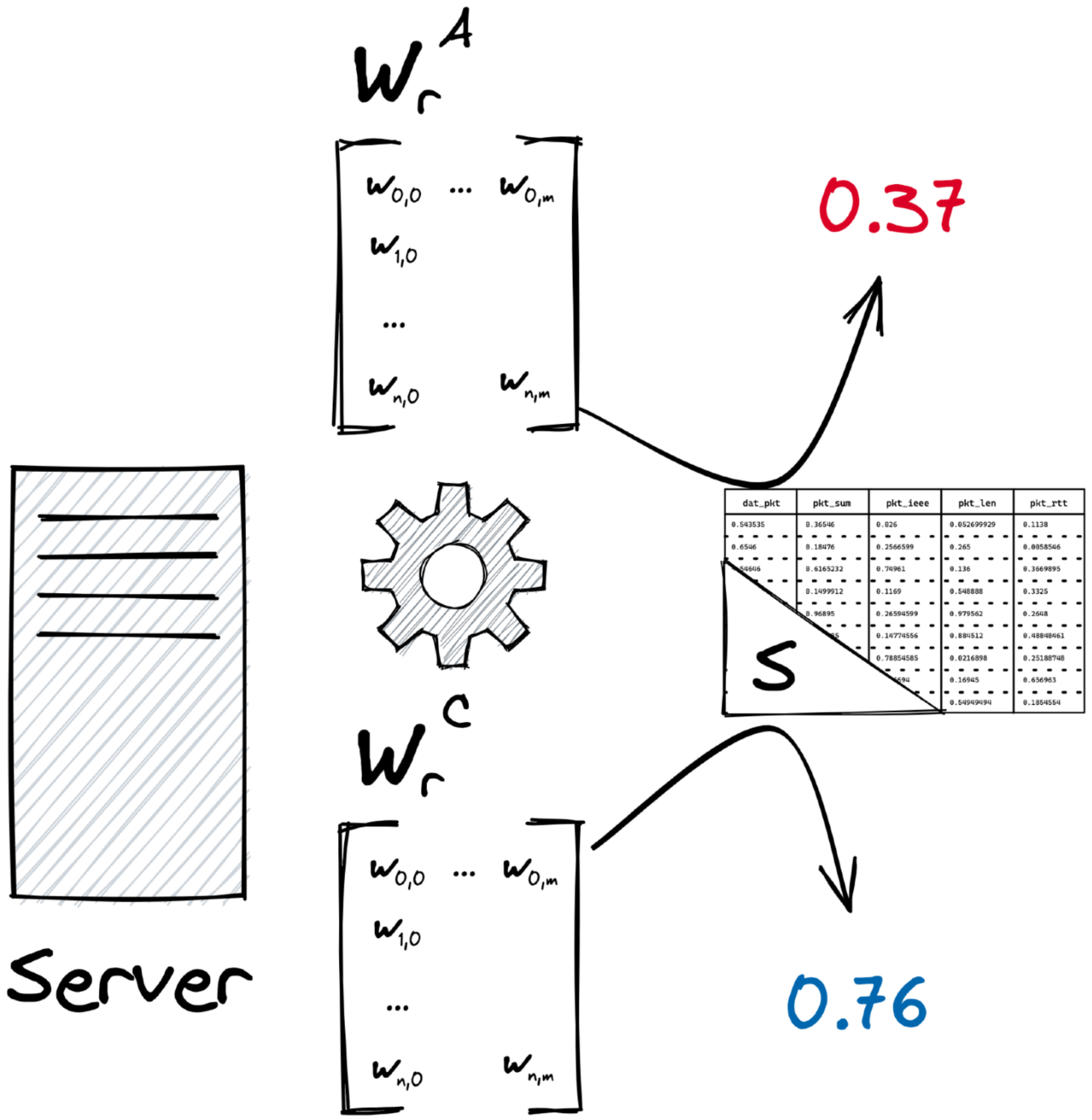
UMR IRISA

SERVER-SIDE EVALUATION [5]



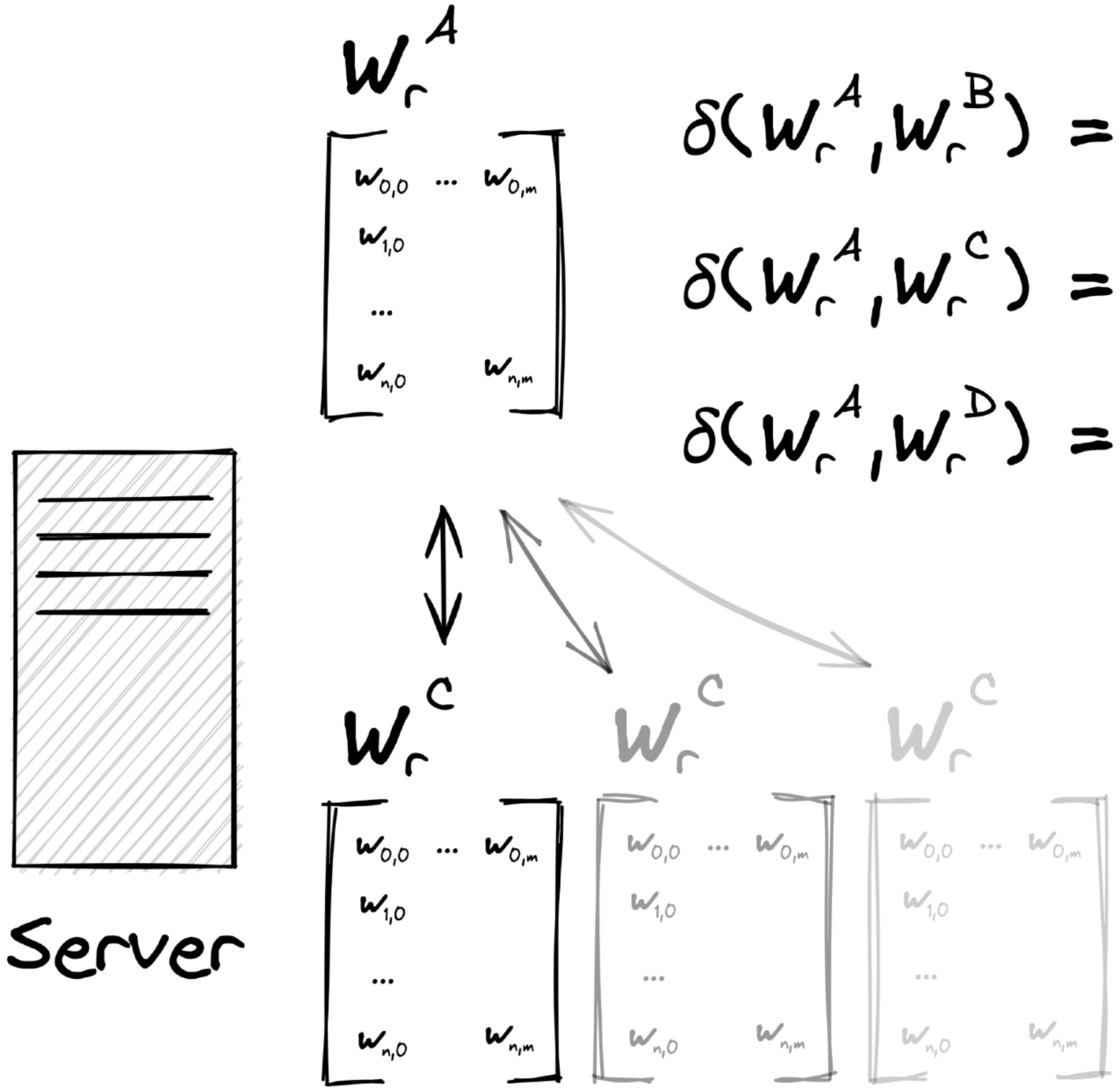


- **Compute test evaluation on updated models**
  - Exclude outlier clients



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

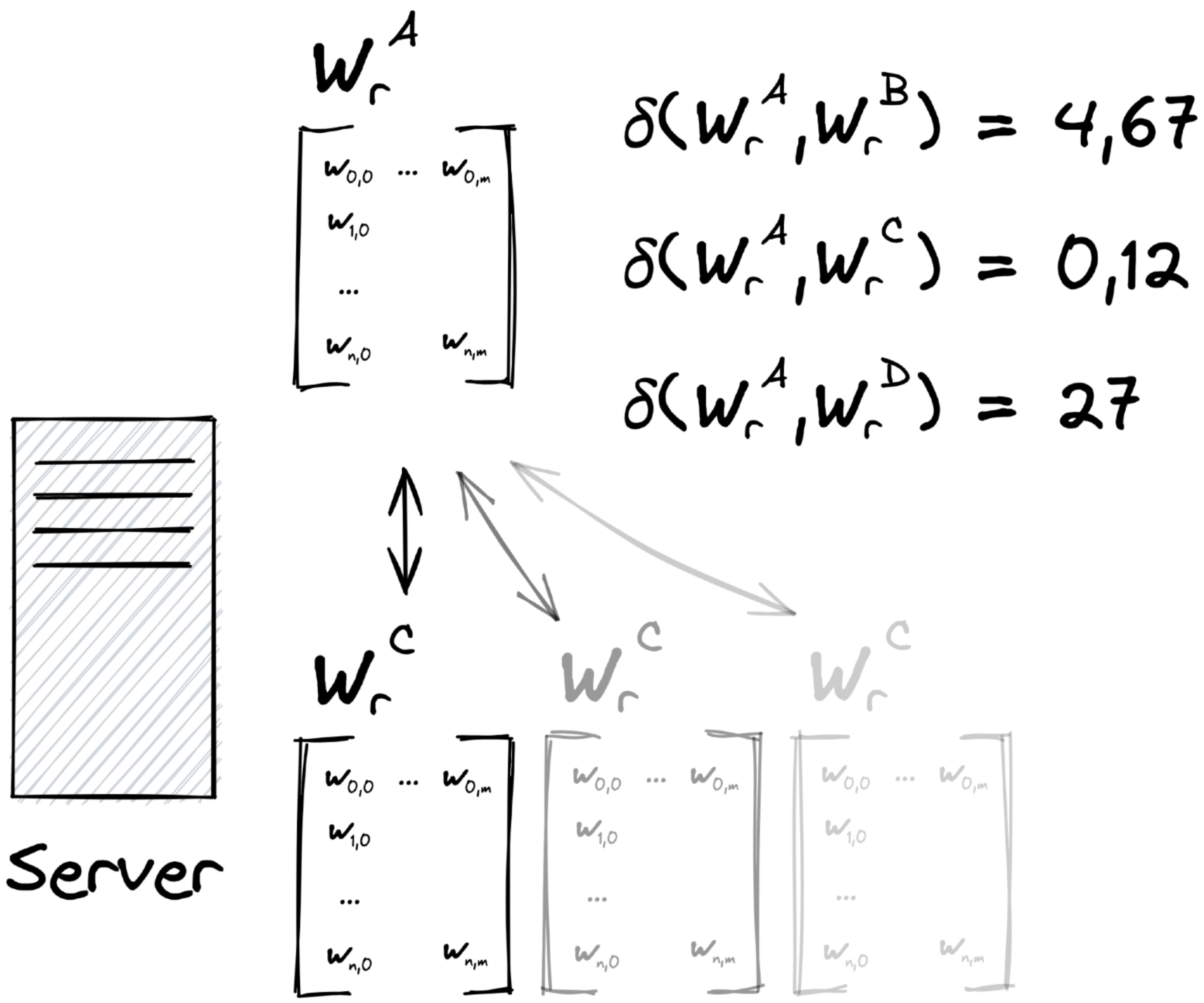
SERVER-SIDE MODEL COMPARISON



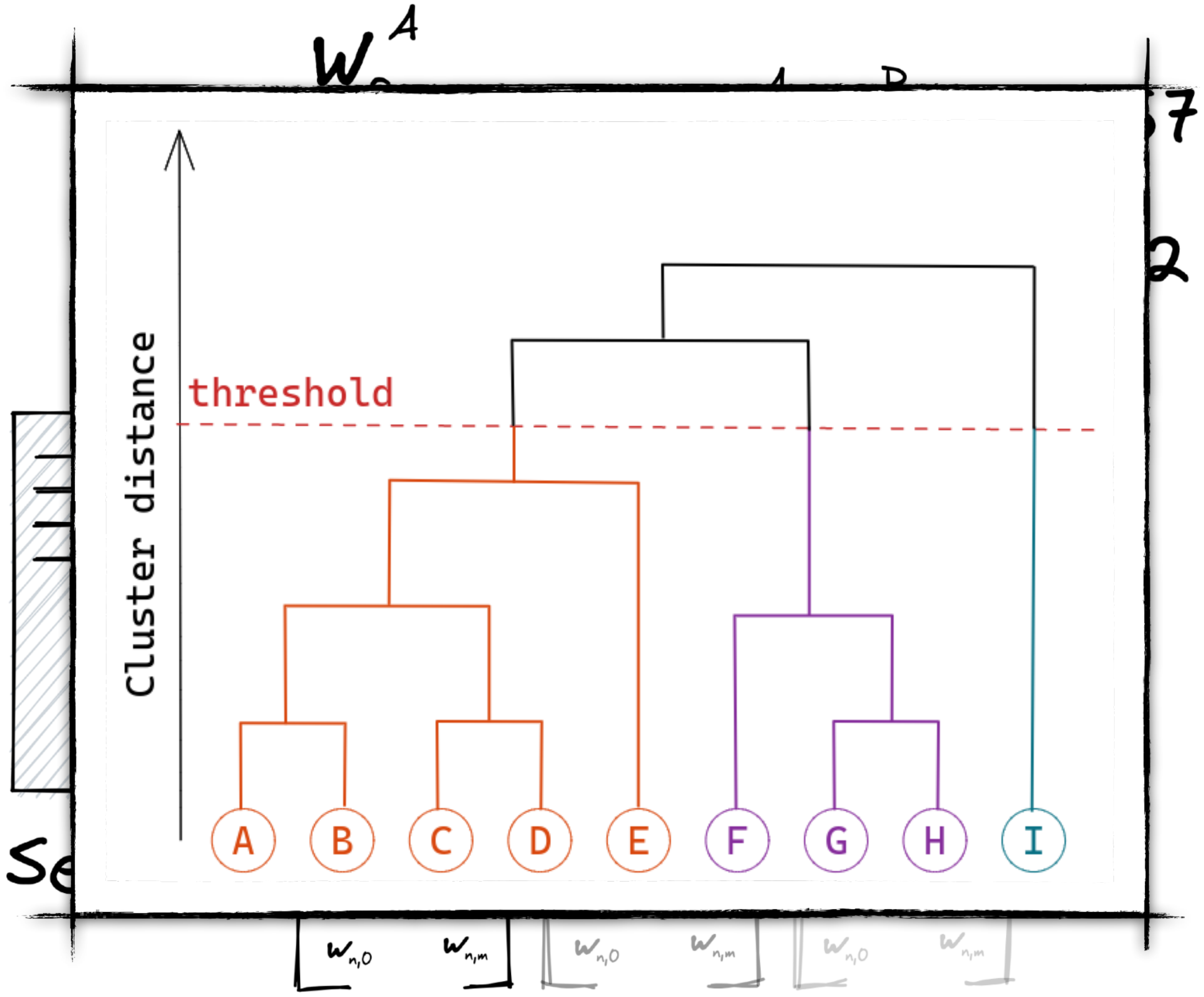
$$\delta(W_r^A, W_r^B) = 4{,}67$$

$$\delta(W_r^A, W_r^C) = 0{,}12$$

$$\delta(W_r^A, W_r^D) = 27$$

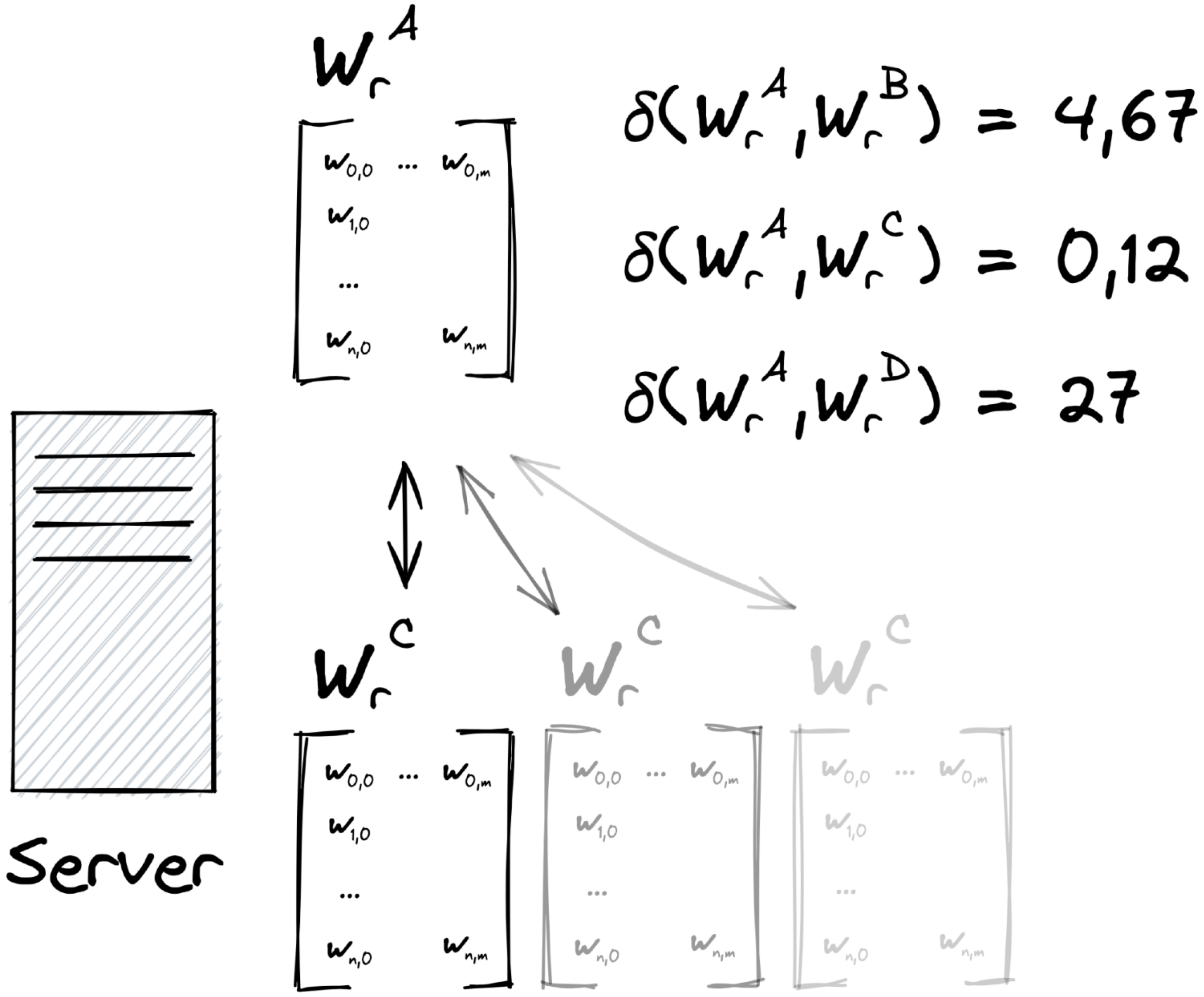


- **Clustering the clients by similarity based on their updates**
  - e.g. Hierarchical clustering [6]



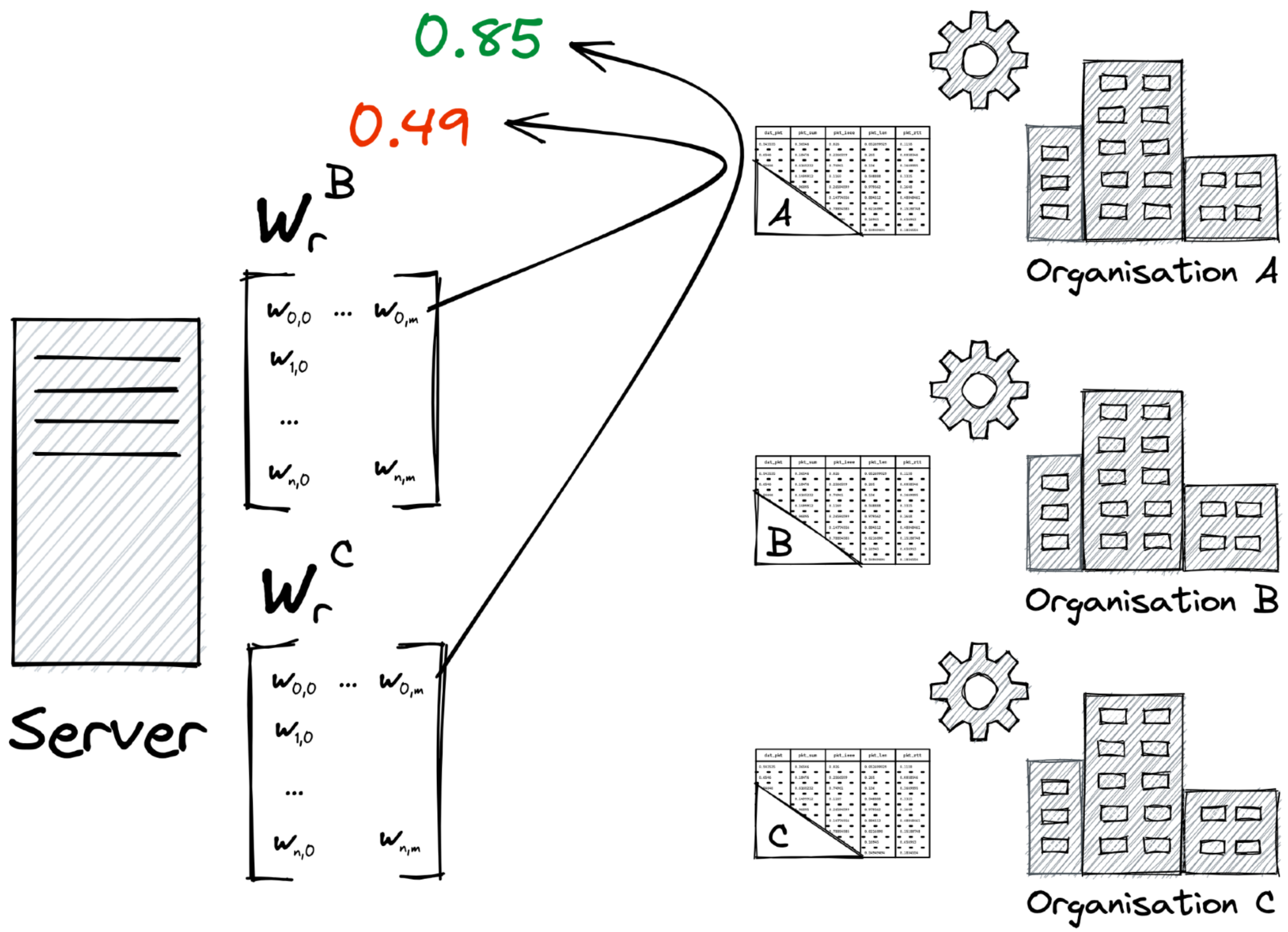
- **Clustering the clients by similarity based on their updates**
  - e.g. Hierarchical clustering [6]

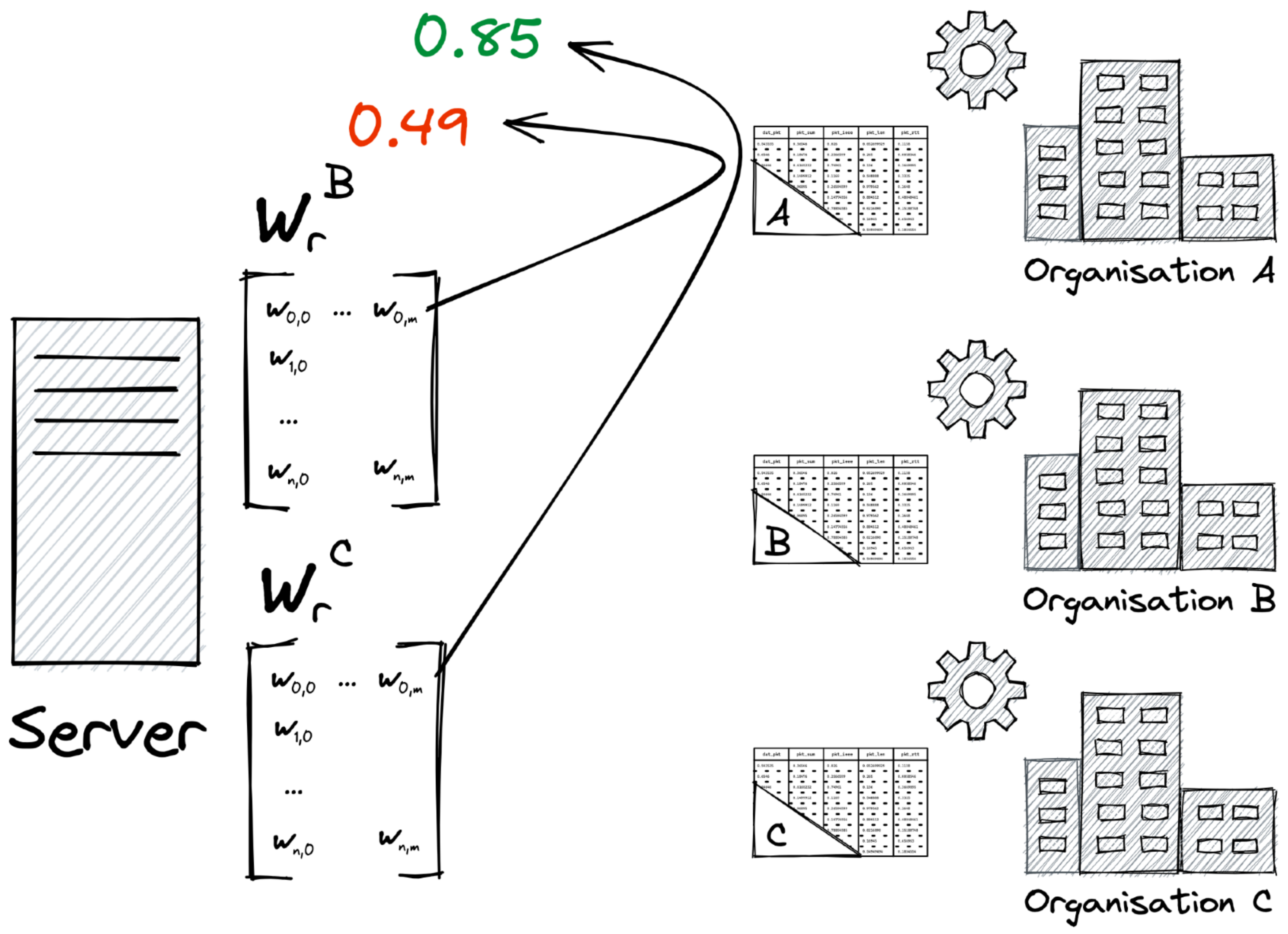
SERVER-SIDE MODEL COMPARISON



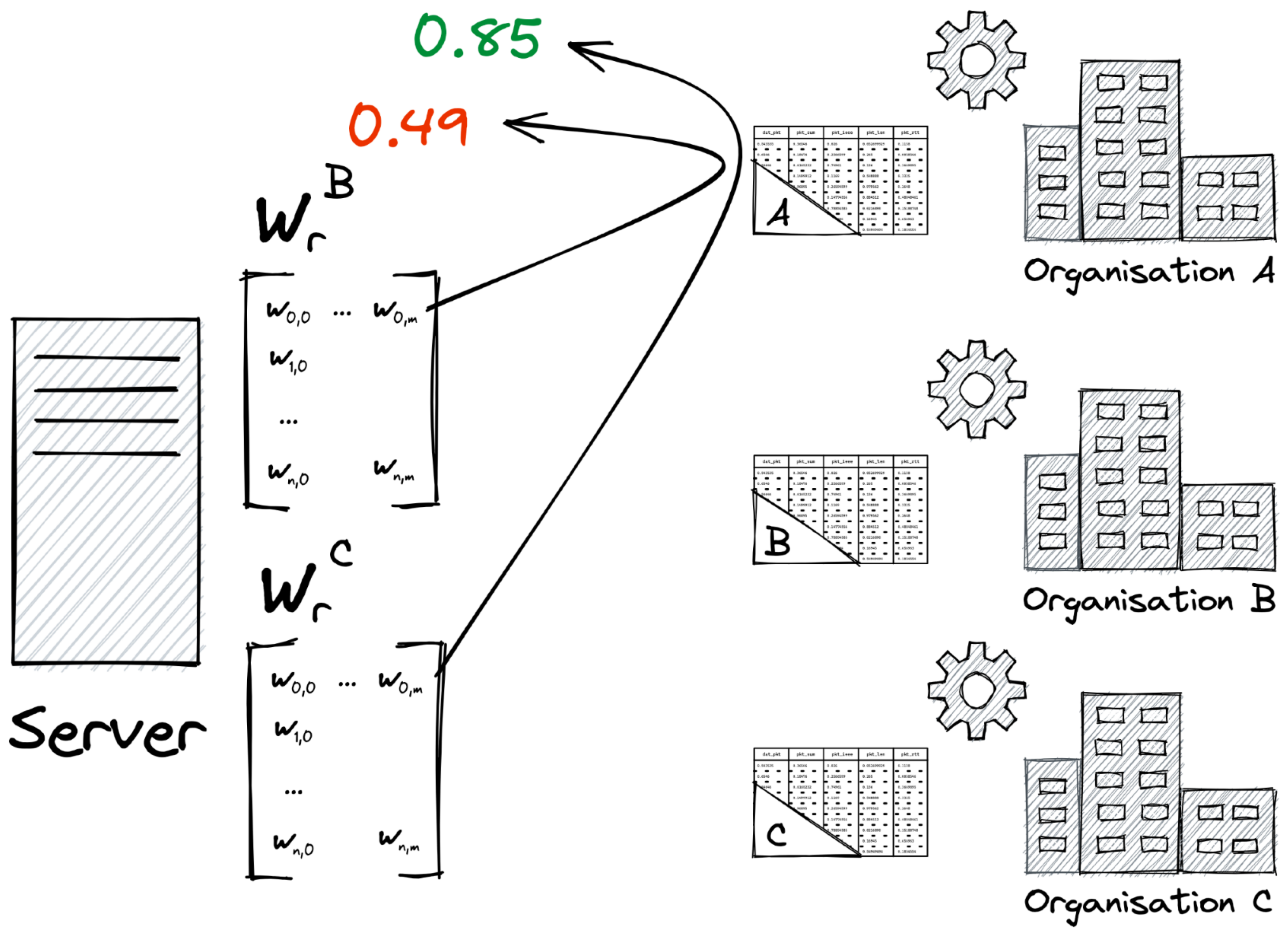
- **Clustering the clients by similarity based on their updates**
  - e.g. Hierarchical clustering [6]
- **Limitation**
  - Less related to client data
  - More appropriated for high-dimensional features

CLIENT-SIDE EVALUATION [7]





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



- **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

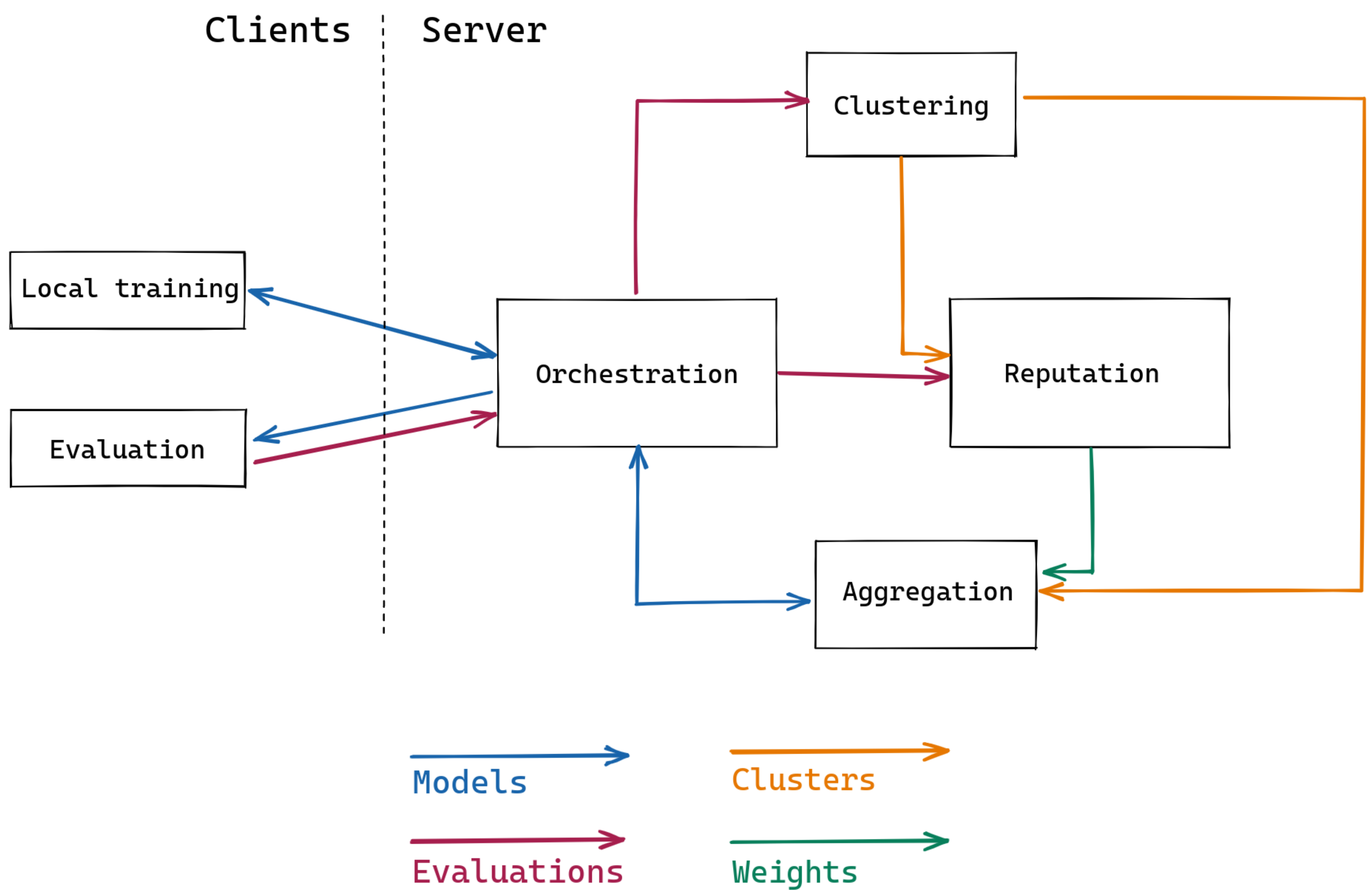
FILTERING CONTRIBUTIONS IN FEDERATED LEARNING FOR INTRUSION DETECTION

JOINT WORK WITH YANN BUSNEL (IMT NORD EUROPE)
LEO LAVAUR, PIERRE-MARIE LECHEVALIER, FABIEN AUTREL, HÉLÈNE LE BOUDER, ROMARIC LUDINARD, MARC-OLIVER PAHL, GÉRALDINE TEXIER (IMT ATLANTIQUE)

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

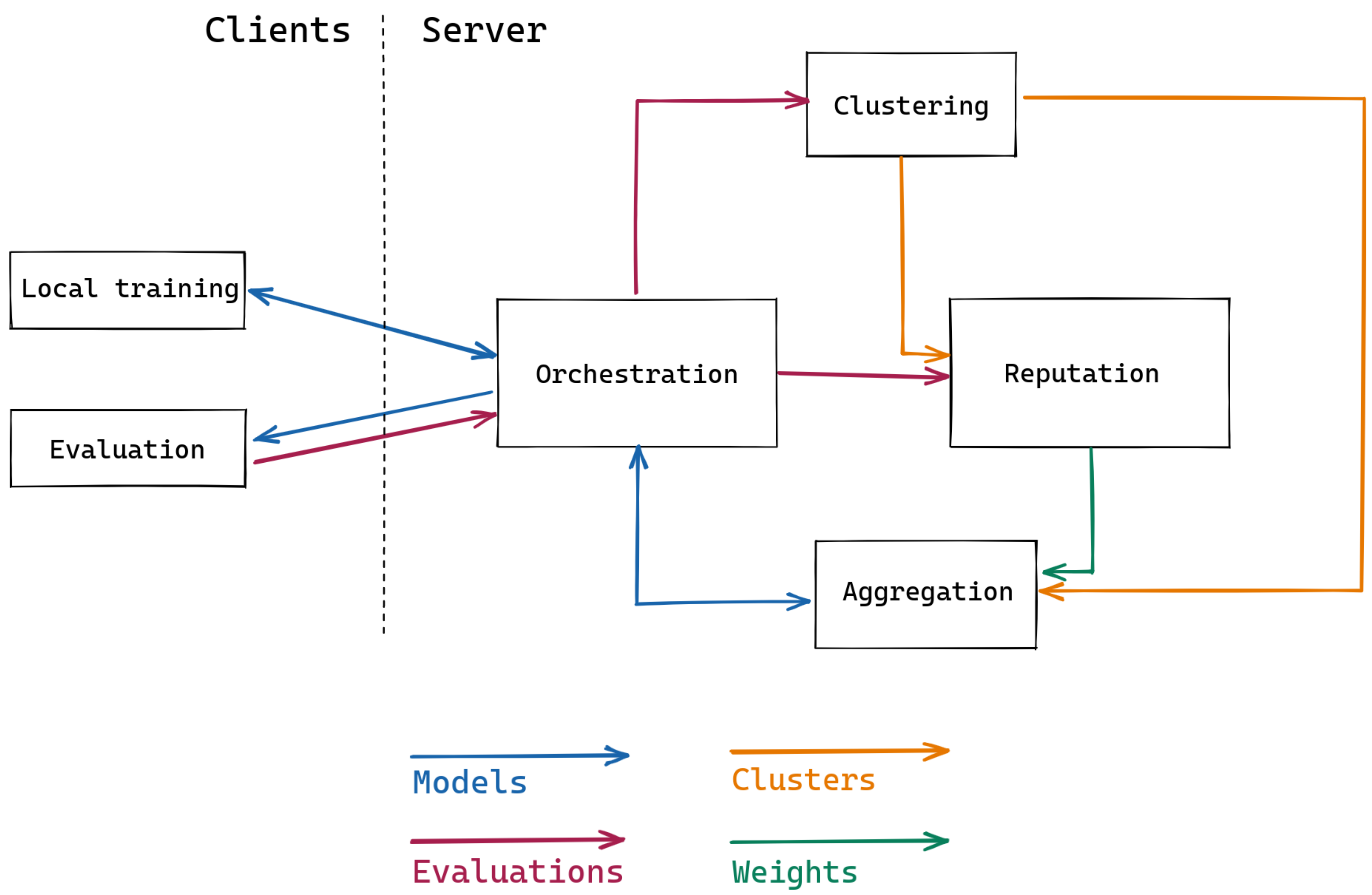
IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

Proposed architecture



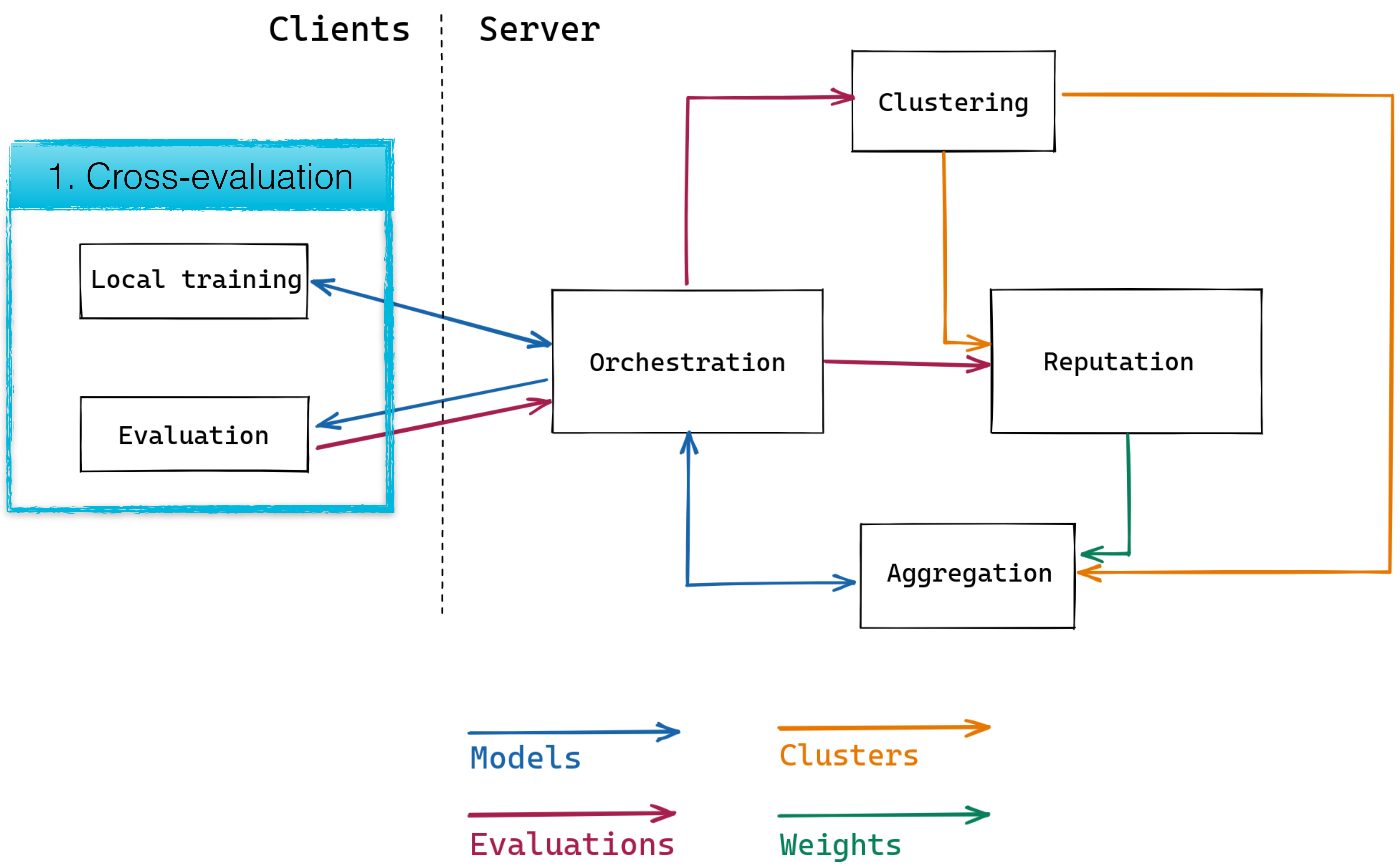
Proposed architecture

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



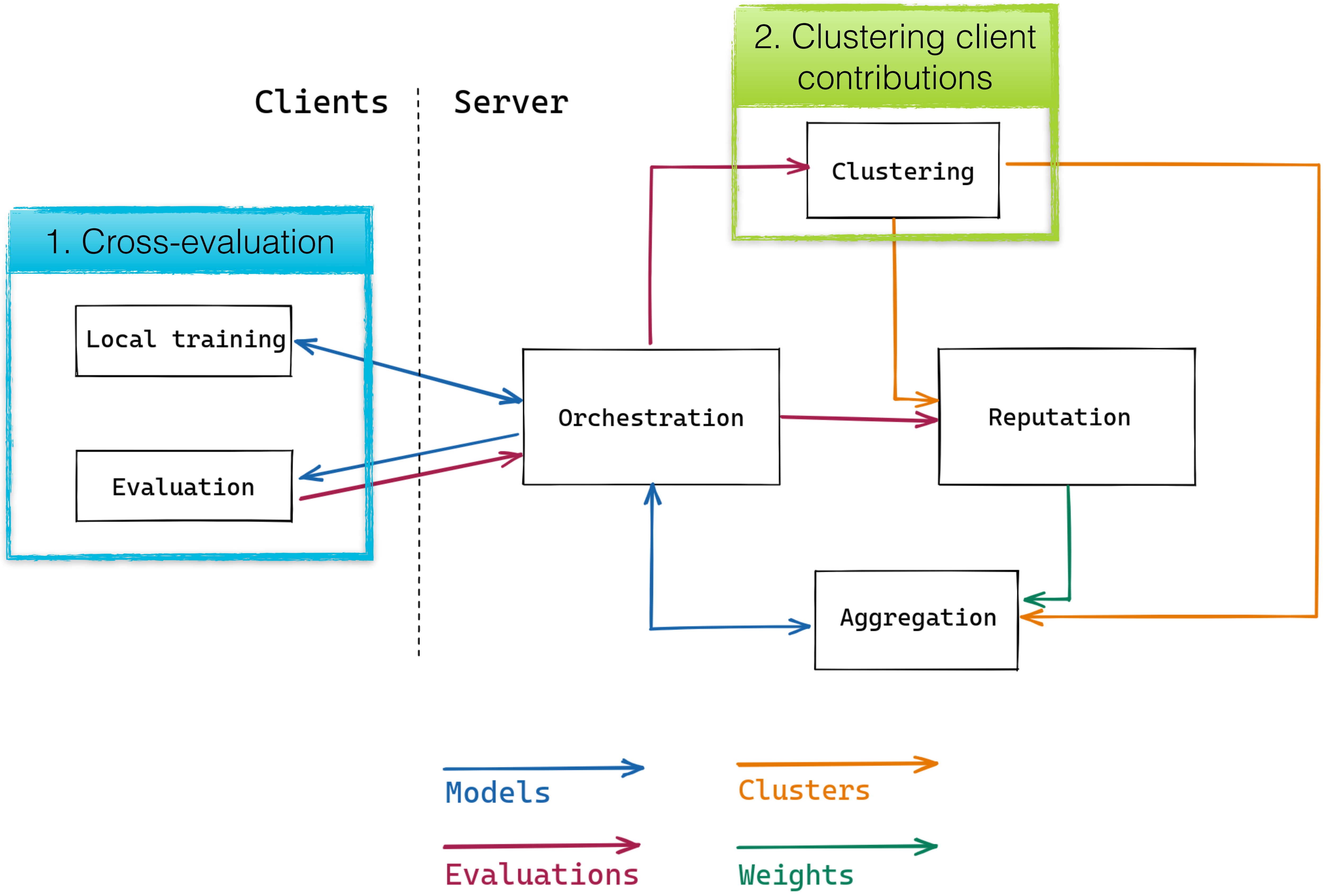
Proposed architecture

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



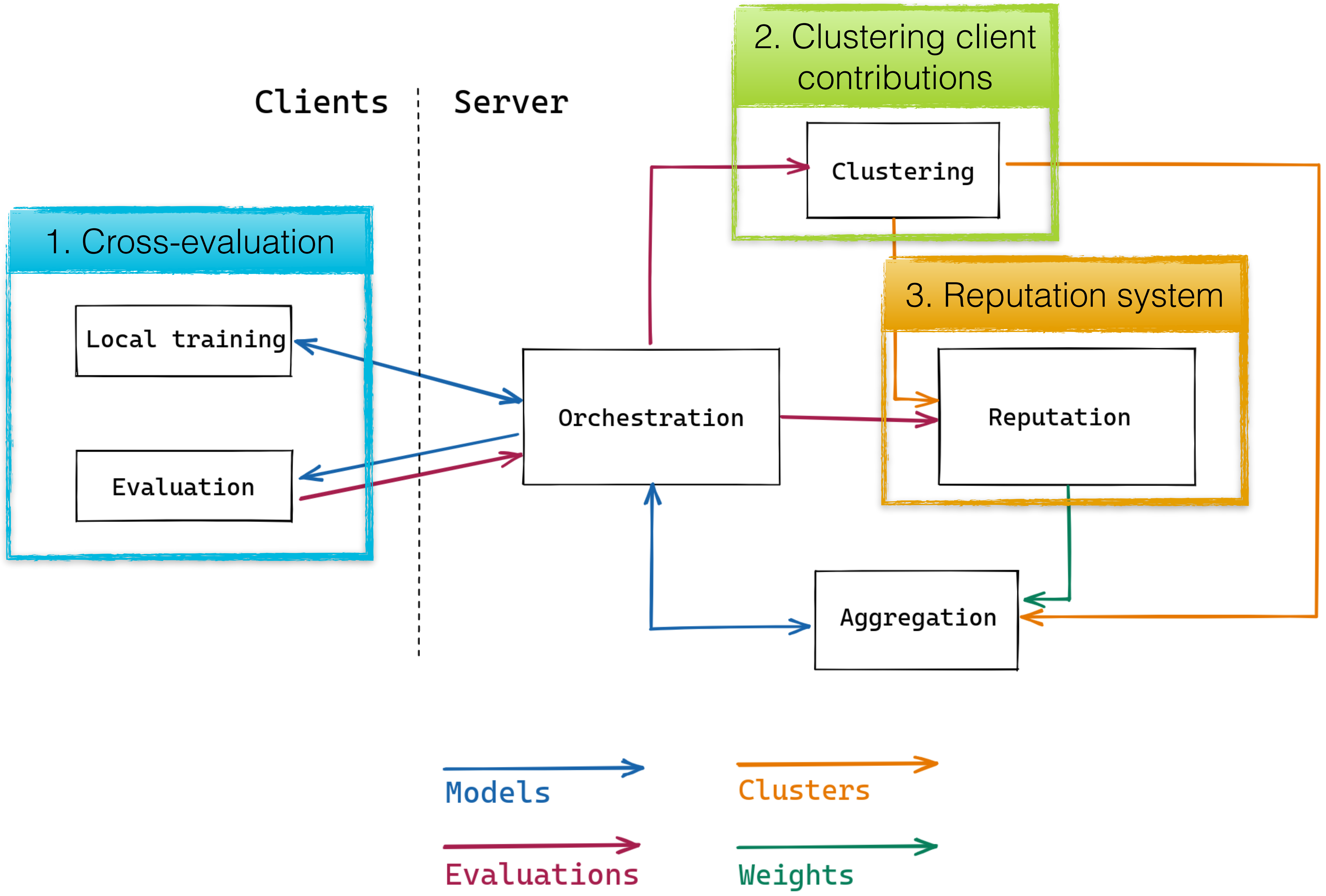
Proposed architecture

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



Proposed architecture

- **Objective:** Mitigate the impact of *bad* contributions to the local models
  - How to evaluate models in highly heterogeneous settings?
  - How to set aside dissimilar participants?
  - How to identify and discard similar but negative behaviors?



HANDS-ON! — PART 3

FEDERATED LEARNING FOR SECURITY

SCAN ME

http://bit.ly/FLxSecu-part3

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

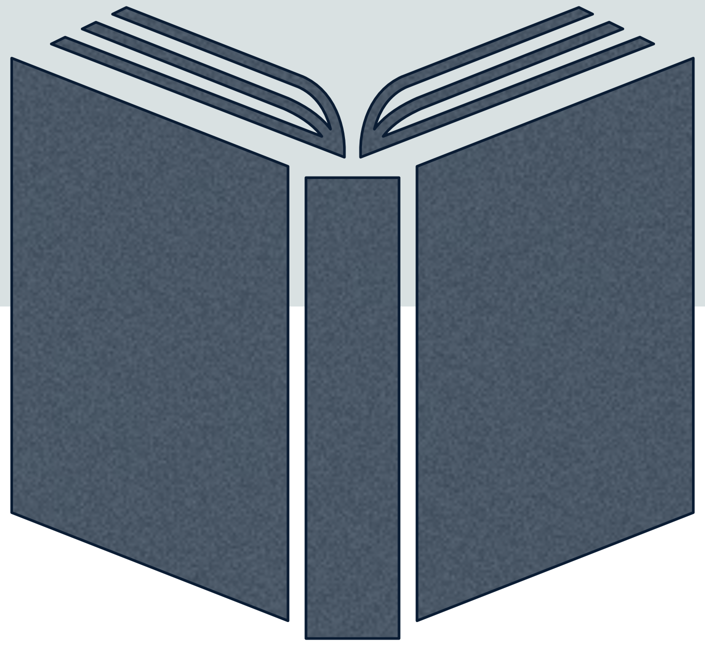
IMT Nord Europe
École Mines-Télécom
IMT-Université de Lille

REFERENCES

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

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

FL REFERENCES



- [1] Thalles Silva. An Introduction to Federated Learning, Encore, 2021.
- [2] Chris J Wallace. Federated Learning, Cloudera Fast Forward Labs, Cloudera, 2019.
- [3] Avi Gopani. Distributed Machine Learning Vs Federated Learning: Which Is Better? Endless Origins, 2021.
- [4] Constantin Philippenko. Federated learning: the privacy-friendly artificial intelligence? Telecom Paris, 2021.
- [5] Aurélien Bellet, Introduction to Federated Learning, Inria, 2020.
- [6] Jianyu Wang, Qinghua Liu, Hao Liang, Gauri Joshi, H. Vincent Poor. Tackling the Objective Inconsistency Problem in Heterogeneous Federated Optimization, 34th Conference on Neural Information Processing Systems (NeurIPS), 2020.
- [7] Min Du. Federated Learning, UC Berkeley, 2019.

APT REFERENCES

- [1] XOSANAVONGSA, Charles. Heterogeneous Event Causal Dependency Definition for the Detection and Explanation of Multi-Step Attacks. 2020. Thèse de doctorat. CentraleSupélec.
- [2] MILAJERDI, Sadegh M., GJOMEMO, Rigel, ESHETE, Birhanu, et al. Holmes: real-time apt detection through correlation of suspicious information flows. In : 2019 IEEE Symposium on Security and Privacy (SP). IEEE, 2019. p. 1137-1152.
- [3] INGALE, Sanjana, PARAYE, Milind, et AMBAWADE, Dayanand. A survey on methodologies for multi-step attack prediction. In : 2020 Fourth International Conference on Inventive Systems and Control (ICISC). IEEE, 2020. p. 37-45.
- [4] PEI, Kexin, GU, Zhongshu, SALTAFORMAGGIO, Brendan, et al. Hercule: Attack story reconstruction via community discovery on correlated log graph. In : Proceedings of the 32Nd Annual Conference on Computer Security Applications. 2016. p. 583-595.
- [5] REN, Hanli, STAKHANOVA, Natalia, et GHORBANI, Ali A. An online adaptive approach to alert correlation. In : International Conference on Detection of Intrusions and Malware, and Vulnerability Assessment. Springer, Berlin, Heidelberg, 2010. p. 153-172.
- [6] LANOE, David, HURFIN, Michel, TOTEL, Eric, et al. An Efficient and Scalable Intrusion Detection System on Logs of Distributed Applications. In : IFIP International Conference on ICT Systems Security and Privacy Protection. Springer, Cham, 2019. p. 49-63.
- [7] ALSAHEEL, Abdulellah, NAN, Yuhong, MA, Shiqing, et al. {ATLAS}: A sequence-based learning approach for attack investigation. In : 30th USENIX Security Symposium (USENIX Security 21). 2021. p. 3005-3022.

FL&IDS REFERENCES

- [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
- [4] L. Lavaur, M.-O. Pahl, Y. Busnel, and F. Autrel, “The Evolution of Federated Learning-based Intrusion Detection and Mitigation: a Survey,” IEEE Trans. On Network and Services Management, Special Issue on Advances in Network Security Management, 2022
- [5] W. Schneble and G. Thamilarasu, “Attack detection using federated learning in medical cyber-physical systems,” International Conference on Computer Communications and Networks, 2019.
- [6] Y. Sun, H. Ochiai, and H. Esaki, “Intrusion Detection with Segmented Federated Learning for Large-Scale Multiple LANs,” 2020 International Joint Conference on Neural Networks (IJCNN), 2020
- [7] M.-O. Pahl and F. X. Aubet, “All Eyes on You: Distributed Multi-Dimensional IoT Microservice Anomaly Detection,” 14th International Conference on Network and Service Management, 2018
- [8] T. D. Nguyen, S. Marchal, M. Miettinen, H. Fereidooni, N. Asokan, and A.-R. Sadeghi, “DÏoT: A Federated Self-learning Anomaly Detection System for IoT,” IEEE 39th International Conference on Distributed Computing Systems (ICDCS), 2019
- [9] S. Rathore, B. Wook Kwon, and J. H. Park, “BlockSecIoT-Net: Blockchain-based decentralized security architecture for IoT network,” Journal of Network and Computer Applications, 2019

FL&IDS REFERENCES

- [10] Y. Fan, Y. Li, M. Zhan, H. Cui, and Y. Zhang, “IoTDefender: A Federated Transfer Learning Intrusion Detection Framework for 5G IoT,” in 2020 IEEE 14th International Conference on Big Data Science and Engineering (BigDataSE), 2020
- [11] S. A. Rahman, H. Tout, C. Talhi, and A. Mourad, “Internet of Things Intrusion Detection: Centralized, On-Device, or Federated Learning?” IEEE Network, 2020
- [12] B. Li, Y. Wu, J. Song, R. Lu, T. Li, and L. Zhao, “DeepFed: Federated Deep Learning for Intrusion Detection in Industrial Cyber-Physical Systems,” IEEE Transactions on Industrial Informatics, 2020
- [13] Y. Chen, J. Zhang, and C. K. Yeo, “Network Anomaly Detection Using Federated Deep Autoencoding Gaussian Mixture Model,” in Machine Learning for Networking, 2020
- [14] T. D. Nguyen, P. Rieger, H. Yalame, H. Mo¨llering, H. Fereidooni, S. Marchal, M. Miettinen, A. Mirhoseini, A.-R. Sadeghi, T. Schneider, and S. Zeitouni. “FLGUARD: Secure and Private Federated Learning.” , arXiv, 2021
- [15] W. Zhang, Q. Lu, Q. Yu, Z. Li, Y. Liu, S. K. Lo, S. Chen, X. Xu, and L. Zhu, “Blockchain-based Federated Learning for Device Failure Detection in Industrial IoT,” IEEE Internet of Things Journal, 2020
- [16] Z. Chen, N. Lv, P. Liu, Y. Fang, K. Chen, and W. Pan, “Intrusion Detection for Wireless Edge Networks Based on Federated Learning,” IEEE Access, 2020
- [17] M. Sarhan, S. Layeghy, and M. Portmann, *Towards a Standard Feature Set for Network Intrusion Detection System Datasets,* arXiv.org, 2021
- [18] G. Bertoli, L. A. Pereira Junior, A. L. dos Santos, O. Saotome, "Generalizing intrusion detection for heterogeneous networks: A stacked-unsupervised federated learning approach," arXiv.org, 2022

POISONING REFERENCES

- [1] Nguyen, T.D., Rieger, P., Miettinen, M. and Sadeghi, A.R. « Poisoning attacks on federated learning-based IoT intrusion detection system ». In Proc. Workshop Decentralized IoT Syst. Secur. (DISS) (pp. 1-7), 2020
- [2] N. Rodríguez-Barroso, D. Jiménez-López, M. V. Luzón, F. Herrera, E. Martínez-Cámara, “Survey on federated learning threats: Concepts, taxonomy on attacks and defences, experimental study and challenges” Elsevier Information Fusion, 2022
- [3] X. Chen, C. Liu, B. Li, K. Lu, D. Song, « Targeted backdoor attacks on deep learning systems using data poisoning », 2017, CoRR abs/1712.05526.
- [4] Y. Gao, B. Gia Doan, Z. Zhang, S. Ma, J. Zhang, A. Fu, S. Nepal, H. Kim. « Backdoor Attacks and Countermeasures on Deep Learning: A Comprehensive Review », 2020, CoRR, abs/2007.10760
- [5] J. Zhou, et al., “A Differentially Private Federated Learning Model against Poisoning Attacks in Edge Computing”, 2022
- [6] C. Briggs, et al., “Federated learning with hierarchical clustering of local updates to improve training on non-IID data”, 2020
- [7] L. Zhao, et al., ”Shielding Collaborative Learning: Mitigating Poisoning Attacks through Client-Side Detection”, 2020
- [8] Y. Huang et al., “Personalized Cross-Silo Federated Learning on Non-IID Data,” AAAI, vol. 35, no. 9, pp. 7865–7873, May 2021, doi: 10.1609/aaai.v35i9.16960.

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

OCTOBER 04TH, 2023
IEEE NOF — IZMIR, TURKEY

THANKS FOR YOUR ATTENTION

FEDERATED LEARNING × SECURITY IN NETWORK MANAGEMENT

yann.busnel@imt-nord-europe.fr
leo.lavaur@imt-atlantique.fr

UMR IRISA