

# SECURITY CONSIDERATIONS FOR MOBILE EDGE COMPUTING

*Rajeev Shorey (PhD)*

*Fellow INAE, Distinguished Scientist ACM  
Distinguished Lecturer, IEEE Future Networks TC*

*CSE Department  
Indian Institute of Technology, Delhi  
India*

LSU

16 November 2023



IEEE  
**Future**  
**NETWORKS™**

Enabling 5G and Beyond

# IEEE Future Networks – FutureNetworks.ieee.org



Collaboration



IEEE Antennas and Propagation Society



IEEE ComSoc™  
IEEE Communications Society



IEEE ELECTRONICS PACKAGING SOCIETY



IEEE TRANSPORTATION SYSTEMS SOCIETY



IEEE Reliability Society



IEEE VTS  
Connecting the Mobile World

Content

IEEE Future Networks Tech Focus  
Issue 16, June 2023

+ technical newsletter, podcasts, videos, articles

Events

IEEE Future Networks™  
WORLD FORUM • 2022

IEEE Connecting the UNCONNECTED™ SUMMIT  
An IEEE Future Networks Program



+ more!

Research & Education

IEEE INGR International Network Generations Roadmap

+ eLearning, webinar series, white papers, tutorials

Join today! [bit.ly/fntc-join](https://bit.ly/fntc-join)

# IEEE Future Networks

Be connected to IEEE Future Networks to shape future network requirements

Get monthly updates on technical workshops, summits, webinars, podcasts, and call for proposals, papers, and volunteer opportunities

**Thousands are already members**

**Join today: [bit.ly/fntc-join](https://bit.ly/fntc-join)**

Enabling 5G and Beyond | [FutureNetworks.ieee.org](https://FutureNetworks.ieee.org)

# Agenda of the Tutorial

- Introduction & Motivation
- Mobile Edge Security (MEC)
- MEC Architecture
- Security issues in Emerging Edge Paradigms
  - *Federated Learning*
  - *Reinforcement Learning*
- Summary and Future Directions

# The Buzz on Edge Computing

## Edge Computing

Edge Computing | News, how-tos, features, reviews, and videos



**DATA CENTER EXPLORER** By Andy Patrizio  
**Intel details FPGA roadmap**



**IBM, Bharti Airtel partner on edge cloud offerings in India**



### McLaren Racing relies on edge computing at Formula 1 tracks

McLaren's Formula 1 racing team securely delivers apps and data to track crews and guests via VMware Workspace ONE.



**DATA CENTER EXPLORER** By Andy Patrizio

### HPE to ship a dedicated inference server for the edge

The small form factor HPE Edgeline EL8000 is designed for AI tasks such as computer vision and natural-language processing.

**Akamai** Products & Solutions Why Akamai Resources

Solutions > Edge Compute

## Edge Compute Solutions

Innovate in real time. With the world's largest serverless compute platform, Akamai puts your code closer to your users.

## Edge Computing

Edge Computing | News, how-tos, features, reviews, and videos



**CLOUD COMPUTING** By David Linthicum

### Cloud computing is reinventing cars and trucks



**CLOUD COMPUTING** By David Linthicum

### The dirty little secret about edge computing



**NEW TECH FORUM**

### Why edge computing matters for modern software development

The next stage of cloud computing brings computing power closer to users, paving the way to better user experiences and more intelligent applications.

# Edge Computing Spend

- Report by Market research firm IDC
- Edge computing spend is expected to surpass \$300 billion by 2026, with a compound annual growth rate of 15% during the three year period
- Edge computing spend to be \$208 billion in 2023, a 13.1% increase on 2022 spend !



# The 5G Vision: Three Broad Use Cases

The three broad use cases include enhanced mobile broadband, mission-critical services and massive IoT

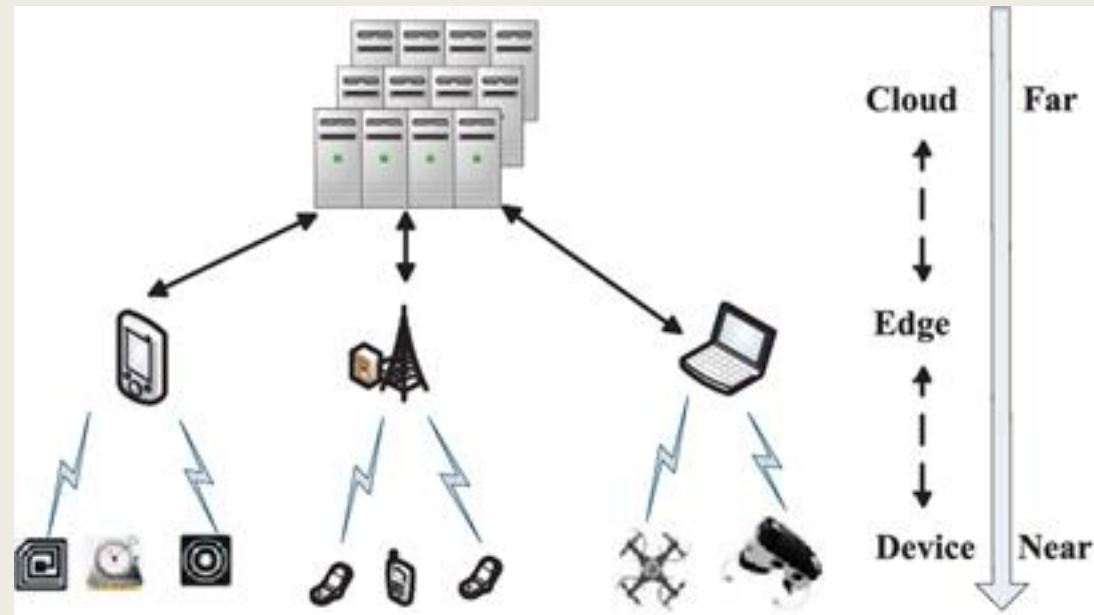
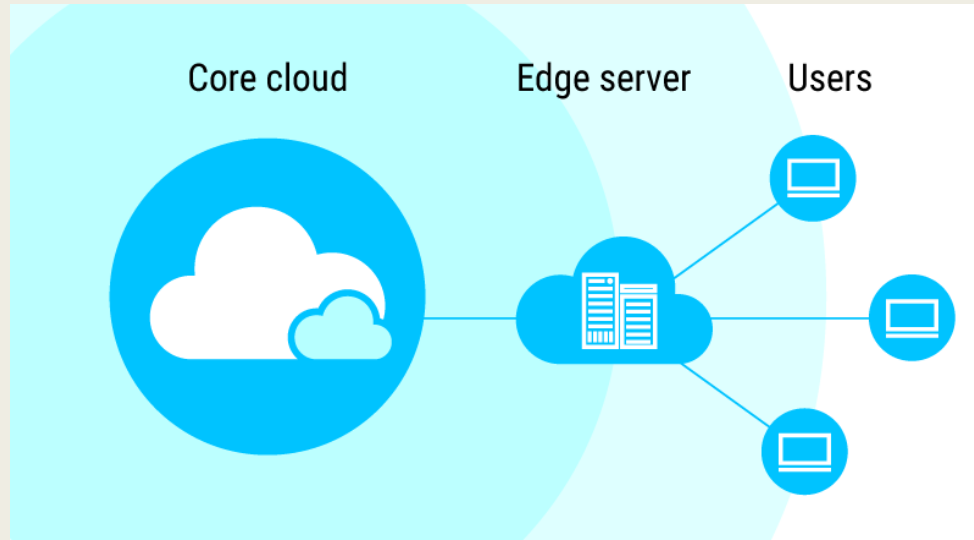


Ref: Leading the World to 5G, Qualcomm Technologies, Inc, 2016

The three broad use cases are characterized by different metrics and parameters

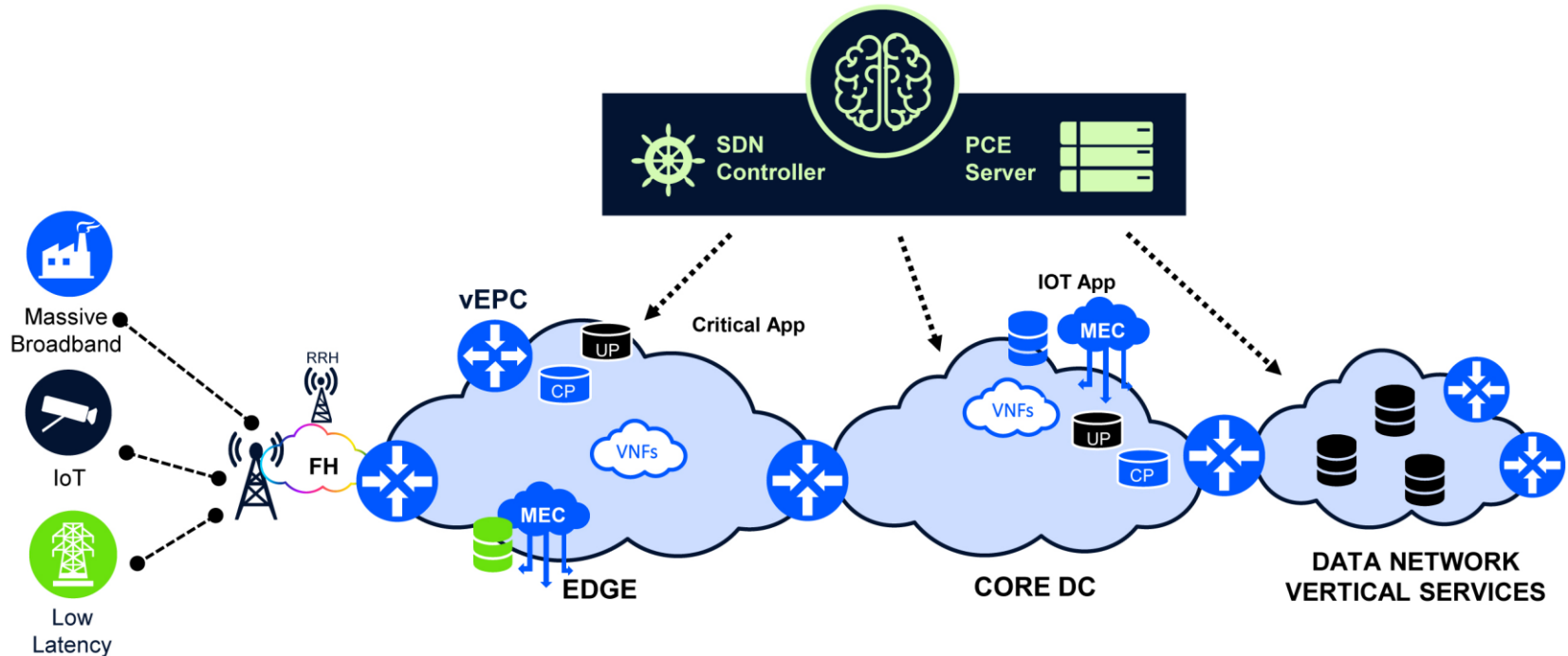


# The Edge Nodes Play a Key Role in Enabling 5G

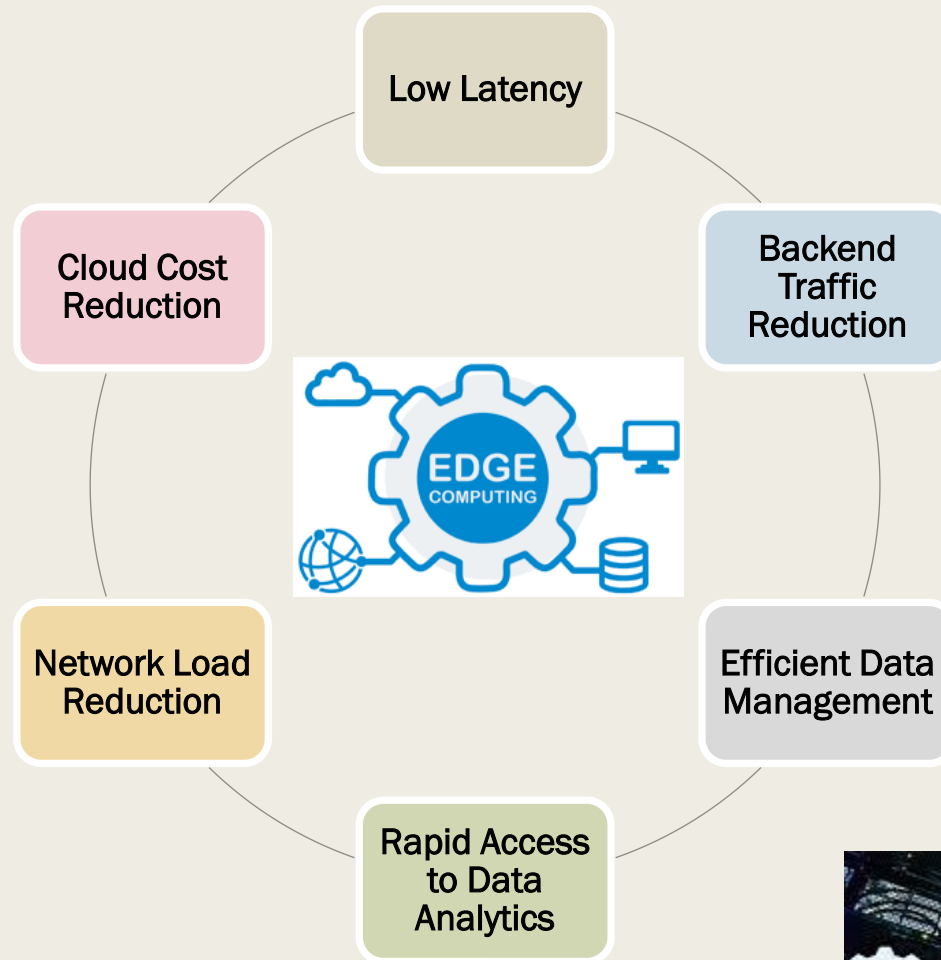


# The 5G Architecture

## 5G ARCHITECTURE DISTRIBUTED CORE, MESH CONNECTIVITY

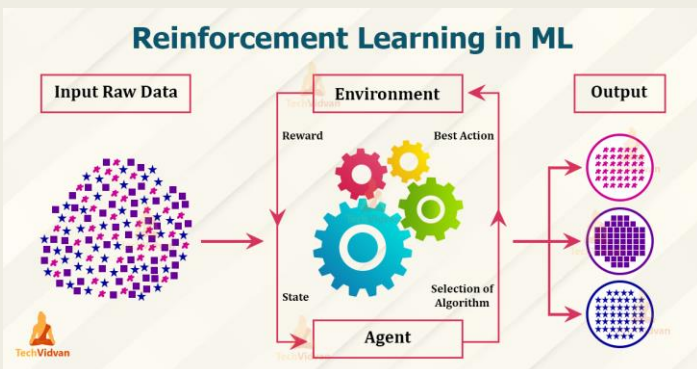
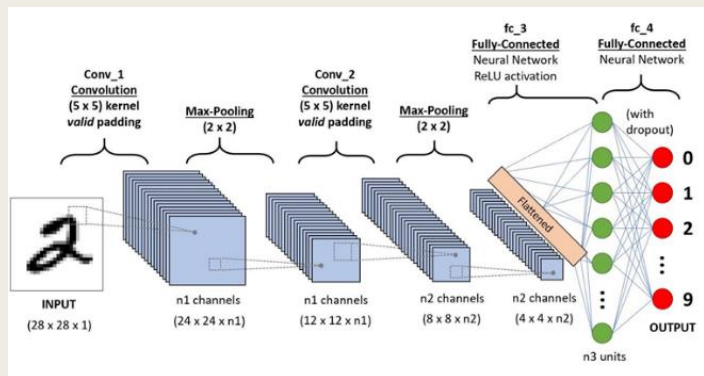
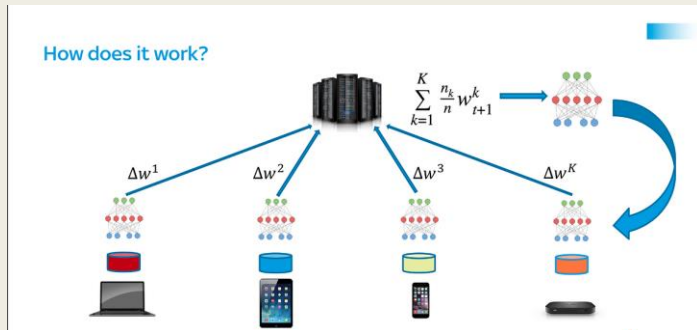


# Edge Computing: Key Advantages



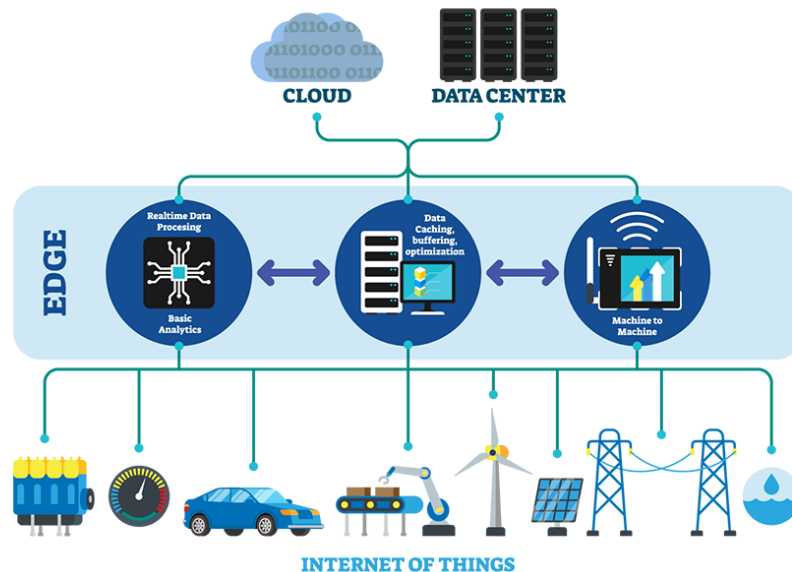
# **AI / ML / Deep Learning at the Edge Nodes**

# Learning at the Resource Constrained Edge Nodes



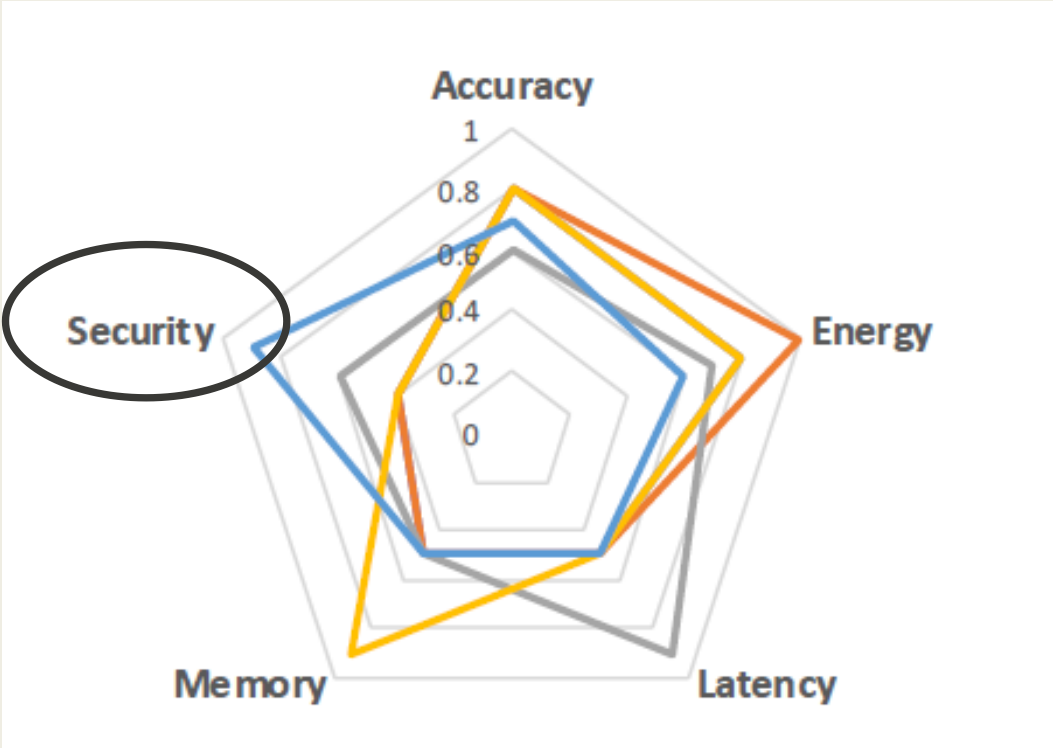
## Resource Constrained Environment

### Edge Computing



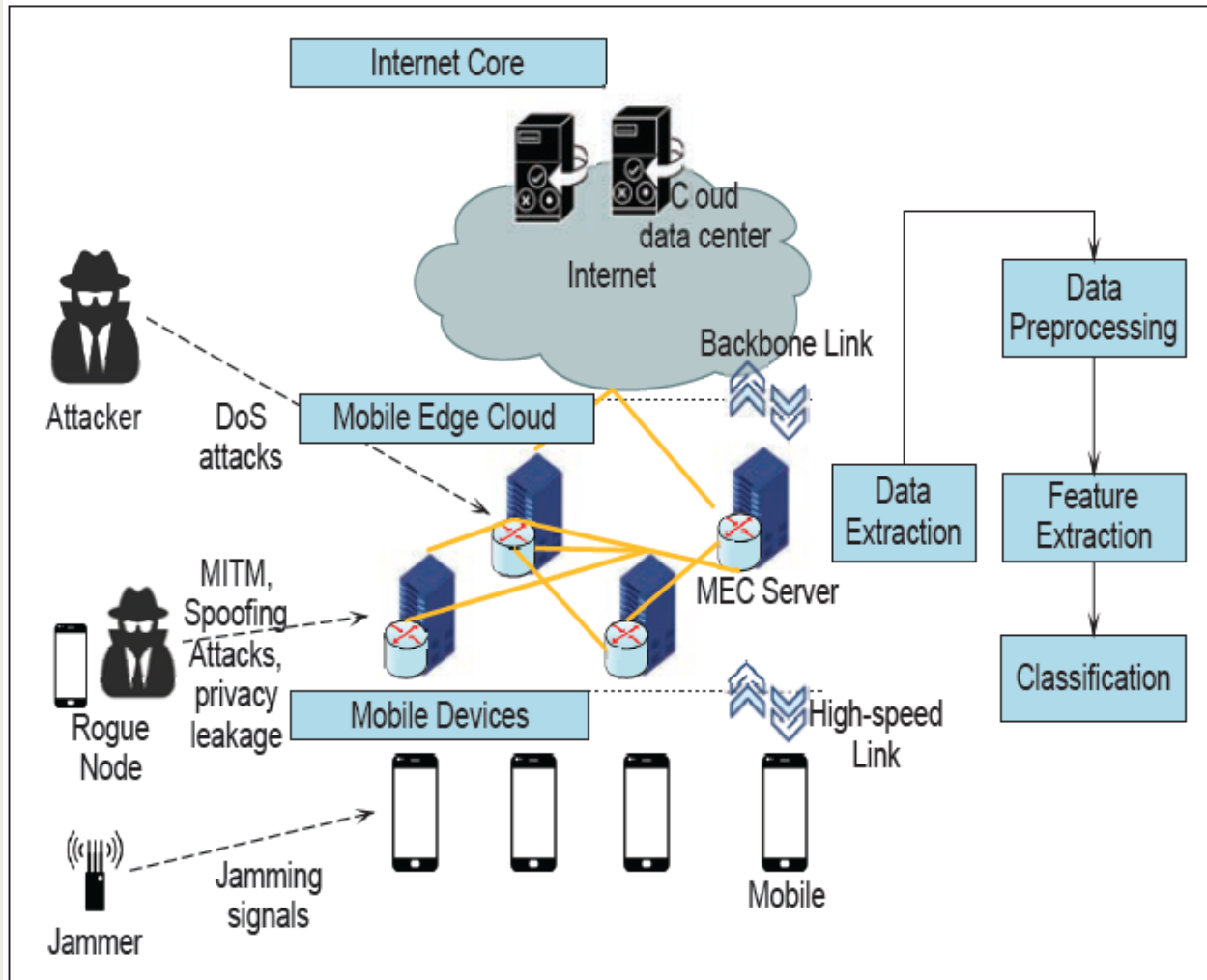
**Security is critical when running ML / DL at the Edge**

# Design Space for Edge Intelligent Systems



# **MEC ARCHITECTURE**

# Secure Three Layer MEC Architecture



Reference: "Security in IoT-Driven Mobile Edge Computing: New Paradigms, Challenges, and Opportunities", S. Garg et al, IEEE Network, Sept/Oct 2021



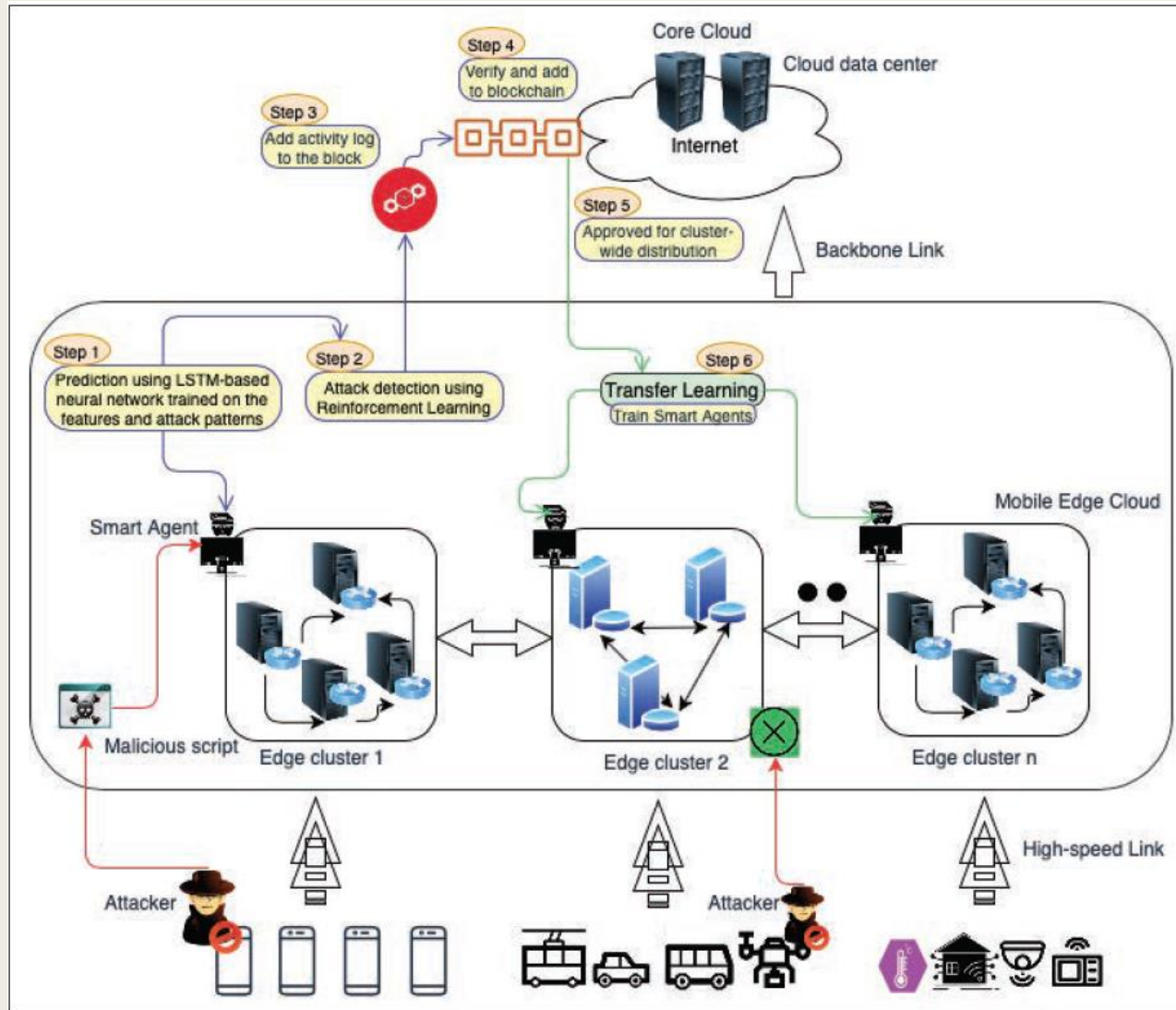
# CHALLENGES TO THE MEC PARADIGM

- Access control
- Heterogeneity of MEC systems
- Identity authentication
- Privacy preservation
- Secure data aggregation
- Mis-configurations
- Diversity of communication technologies
- Secure content distribution
- Resilience to attacks
- Lightweight protocol design
- Establishing trustworthy data sharing practices

# CHALLENGES TO THE MEC PARADIGM

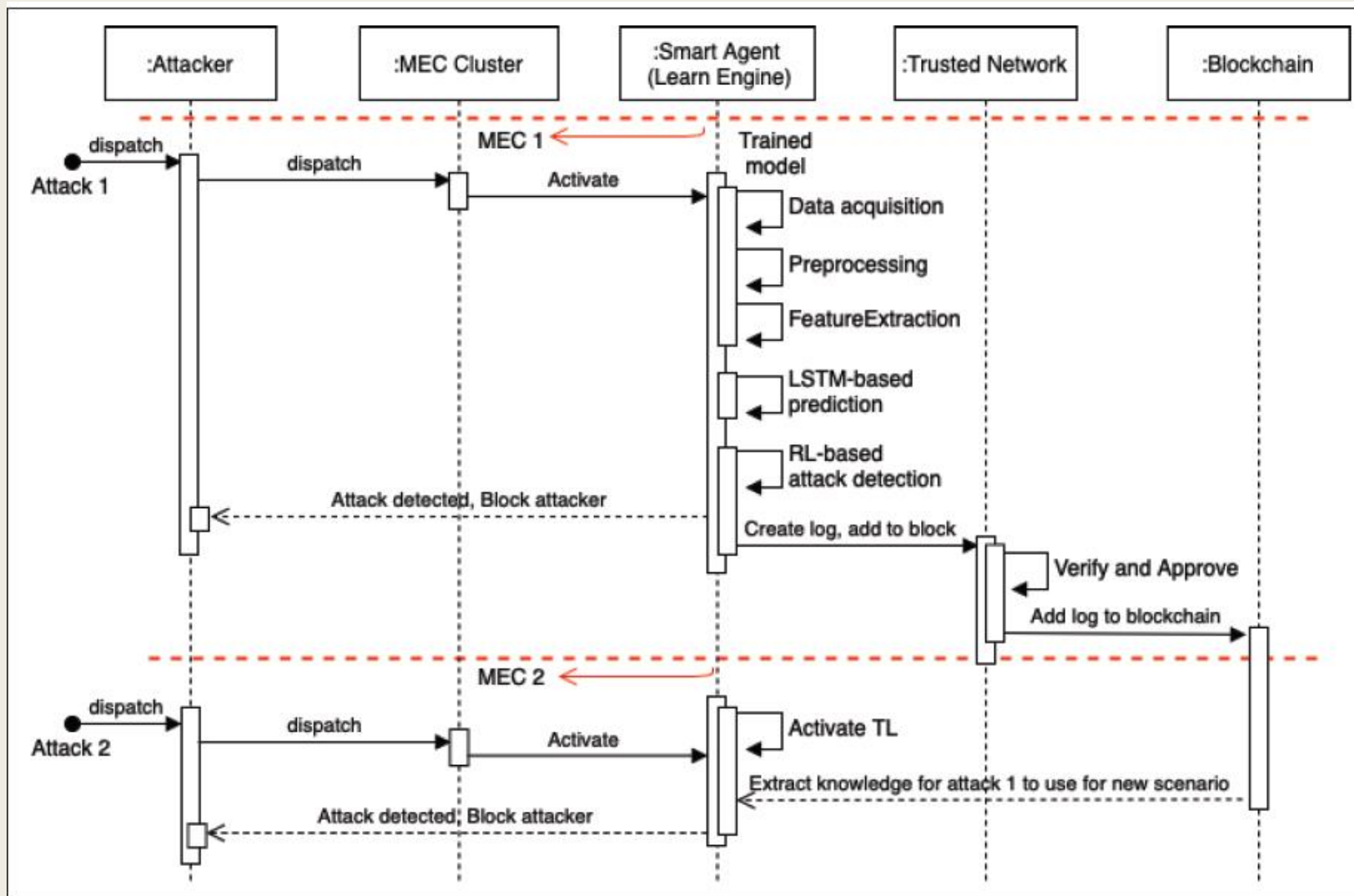
- The *lack of comprehensive security mechanisms* render the deployment of MEC a technically challenging problem
- The security goals of MEC should be grounded on a combined objective of securing the data and ensuring the safety and resiliency of systems and processes
  - Confidentiality
  - Integrity
  - Availability
  - Safety
  - Resiliency

# Proposed SecEdge-Learn MEC Architecture



Reference: "Security in IoT-Driven Mobile Edge Computing: New Paradigms, Challenges, and Opportunities", S. Garg et al, IEEE Network, Sept/Oct 2021

# Sequence of Activities in SecEdge-Learn



Reference: "Security in IoT-Driven Mobile Edge Computing: New Paradigms, Challenges, and Opportunities", S. Garg et al, IEEE Network, Sept/Oct 2021

**EMERGING PARADIGMS AT THE EDGE**

***FEDERATED LEARNING***

***A PRIVACY PRESERVING PARADIGM***

# The Buzz on Federated Learning

Google is using federated learning to improve Assistant's "Hey Google" accuracy

.iReportLinker

The Global Federated Learning Market size is expected to reach \$198.7 Million by 2028, rising at a market growth of 11.1% CAGR during the forecast period

## MIT News

ON CAMPUS AND AROUND THE WORLD



### Collaborative machine learning that preserves privacy

Researchers increase the accuracy and efficiency of a machine-learning method that safeguards user data.

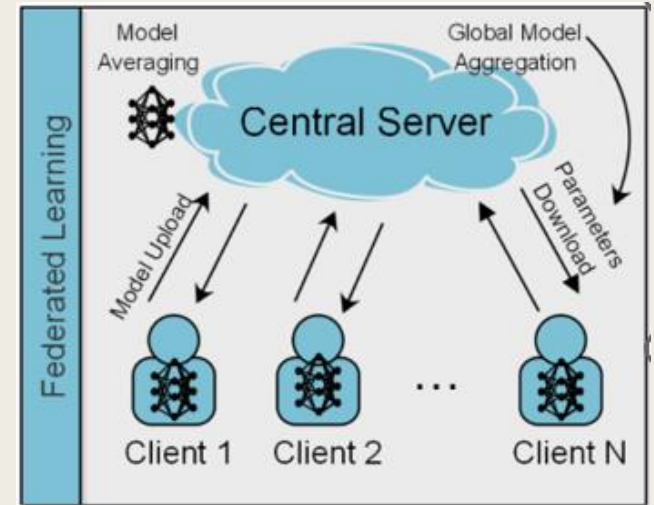
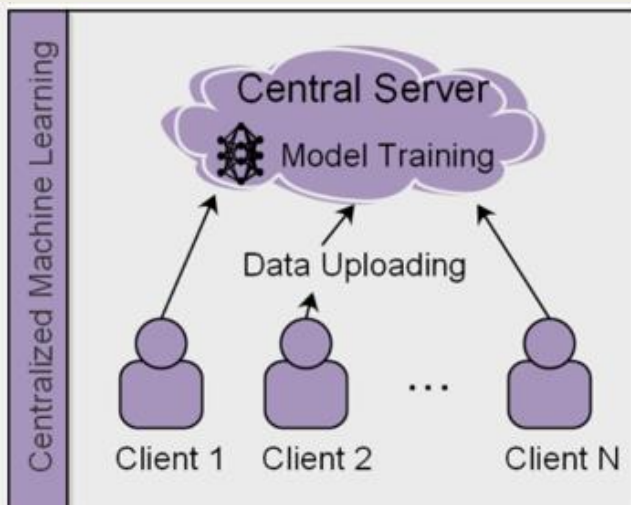
Adam Zewe | MIT News Office  
September 7, 2022

# Applications of Federated Learning

- Application in the Healthcare Industry
- Applications for FinTech
- Applications in Insurance Sector
- Applications in IoT
- Application in other Industries and Technologies

# CLASSICAL MACHINE LEARNING VERSUS FEDERATED LEARNING

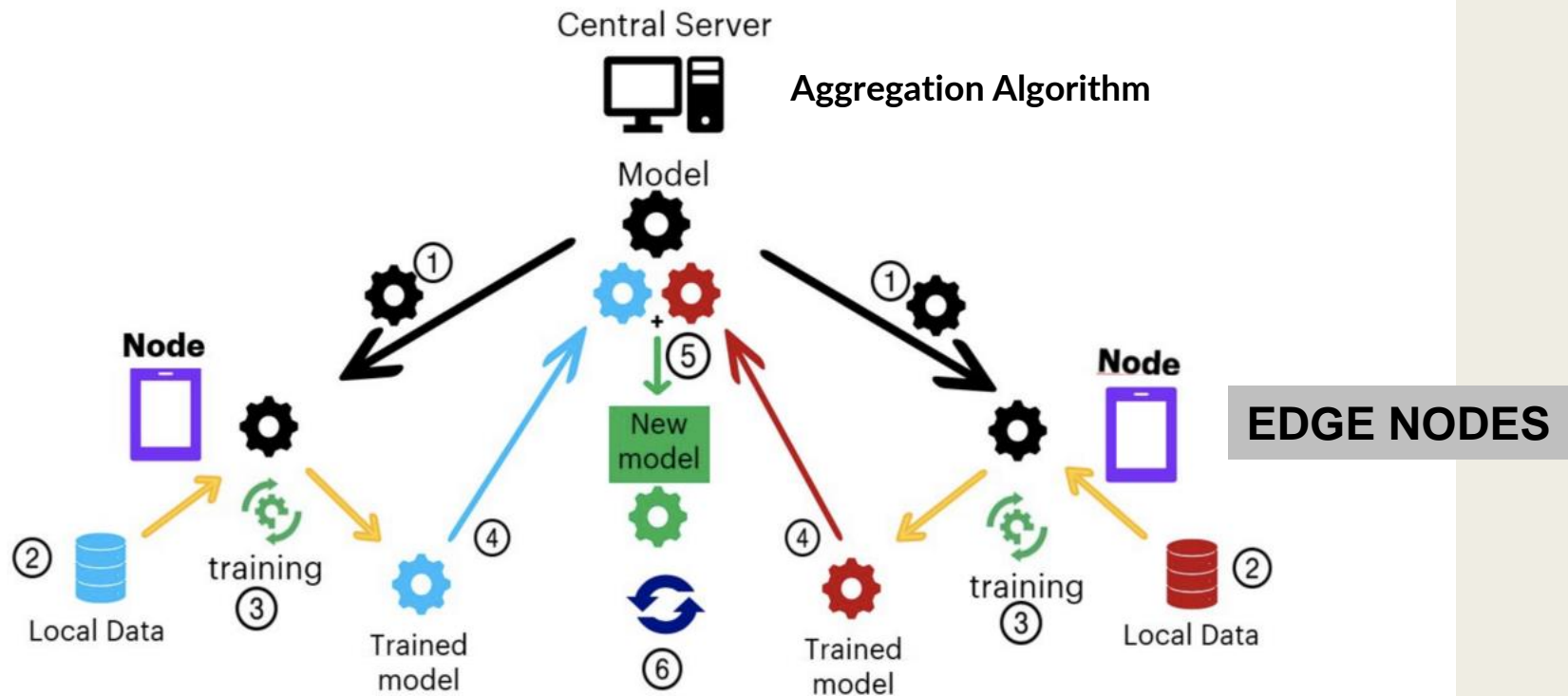
- Central machine learning
  - move the data to the computation
- Federated (machine) learning
  - move the computation to the data





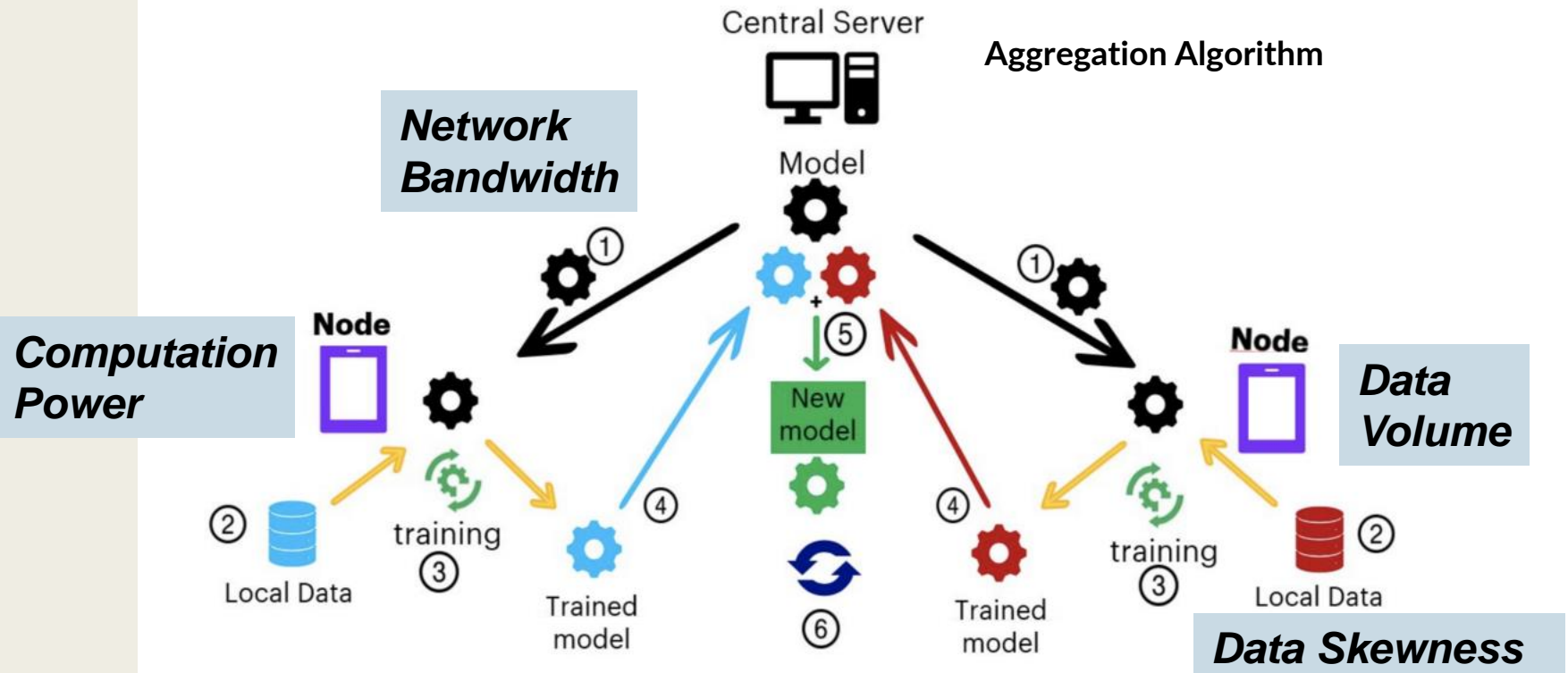
# Federated Learning

Distributed System with ML Model Exchange



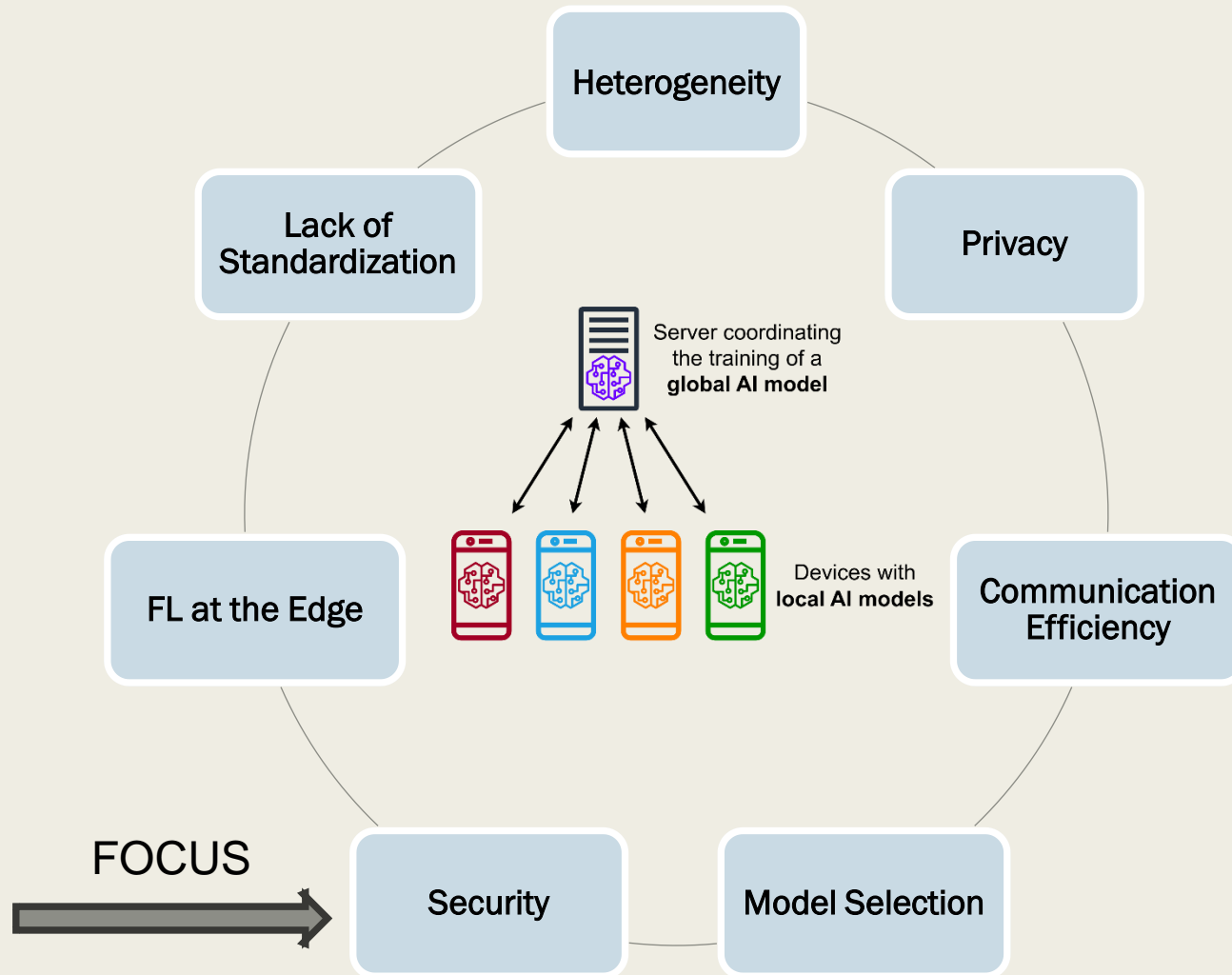
***FL Key Objective: Privacy Preserving Paradigm !***

# Federated Learning & Network Parameters



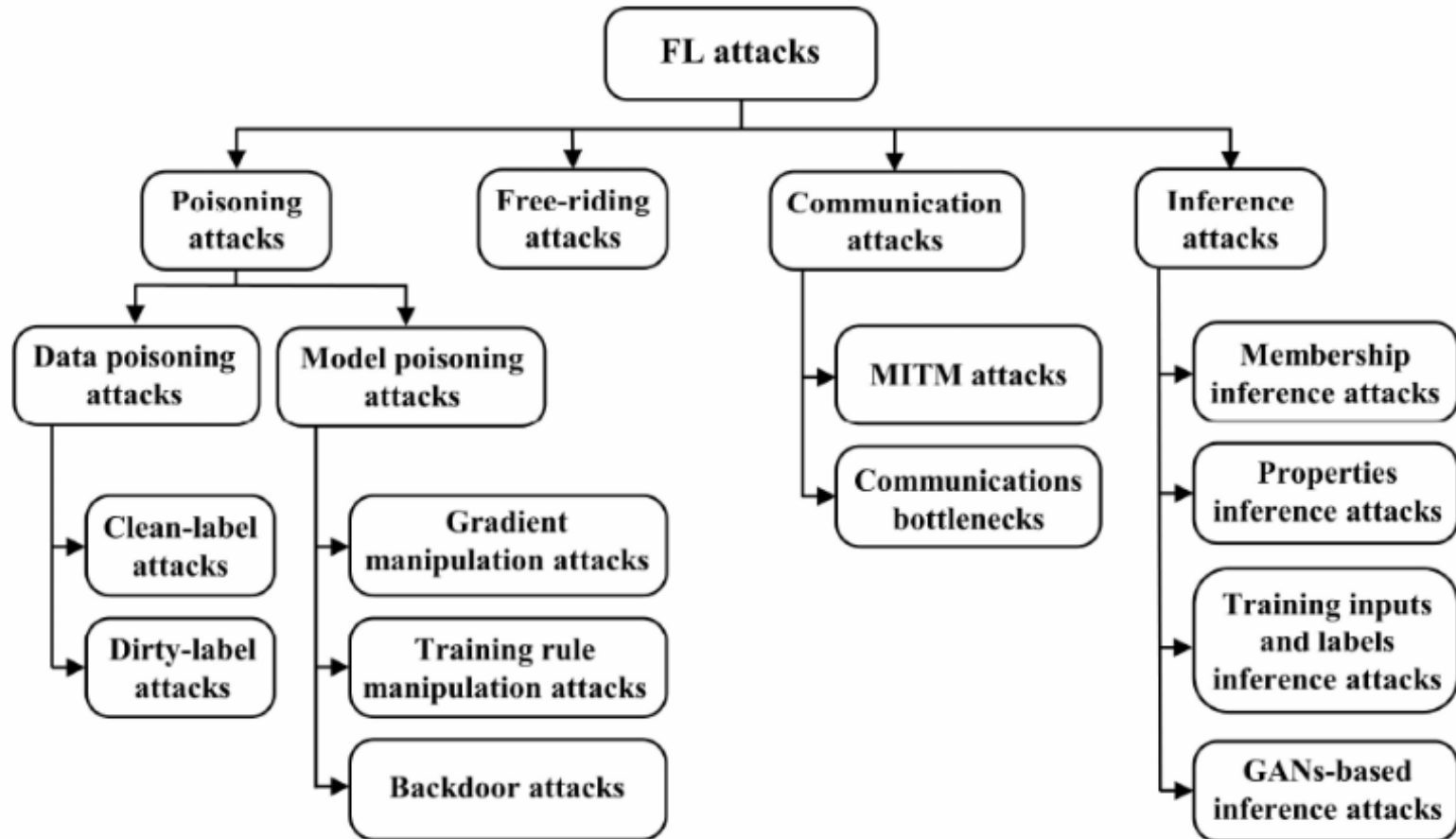
***FL Performance is also a function of the System Parameters***

# Challenges of Federated Learning

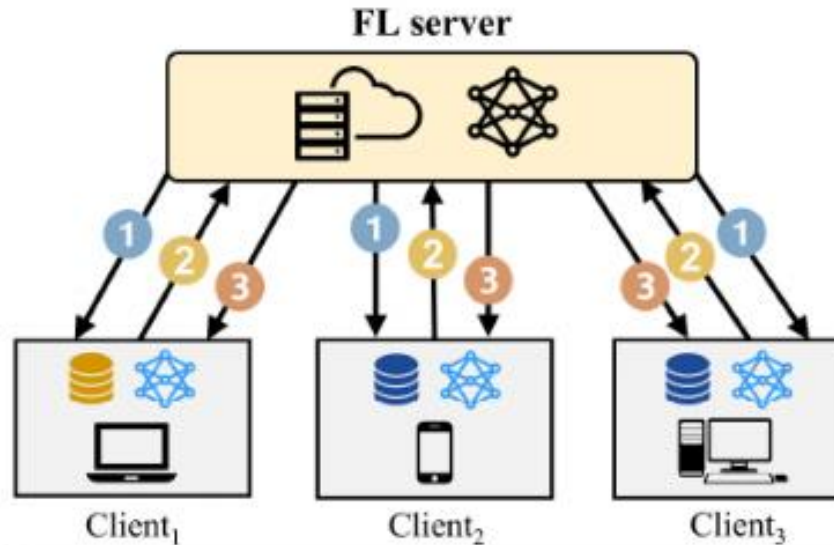


# Threats, Attacks and Defences in Federated Learning

# Taxonomy of Attacks on Federated Learning Systems



# Attack Vectors in Federated Learning



**Step 1:** Model initialization.

**Step 2:** Local model training and upload.

**Step 3:** Global model aggregation and update.

# Attack Vectors in Federated Learning

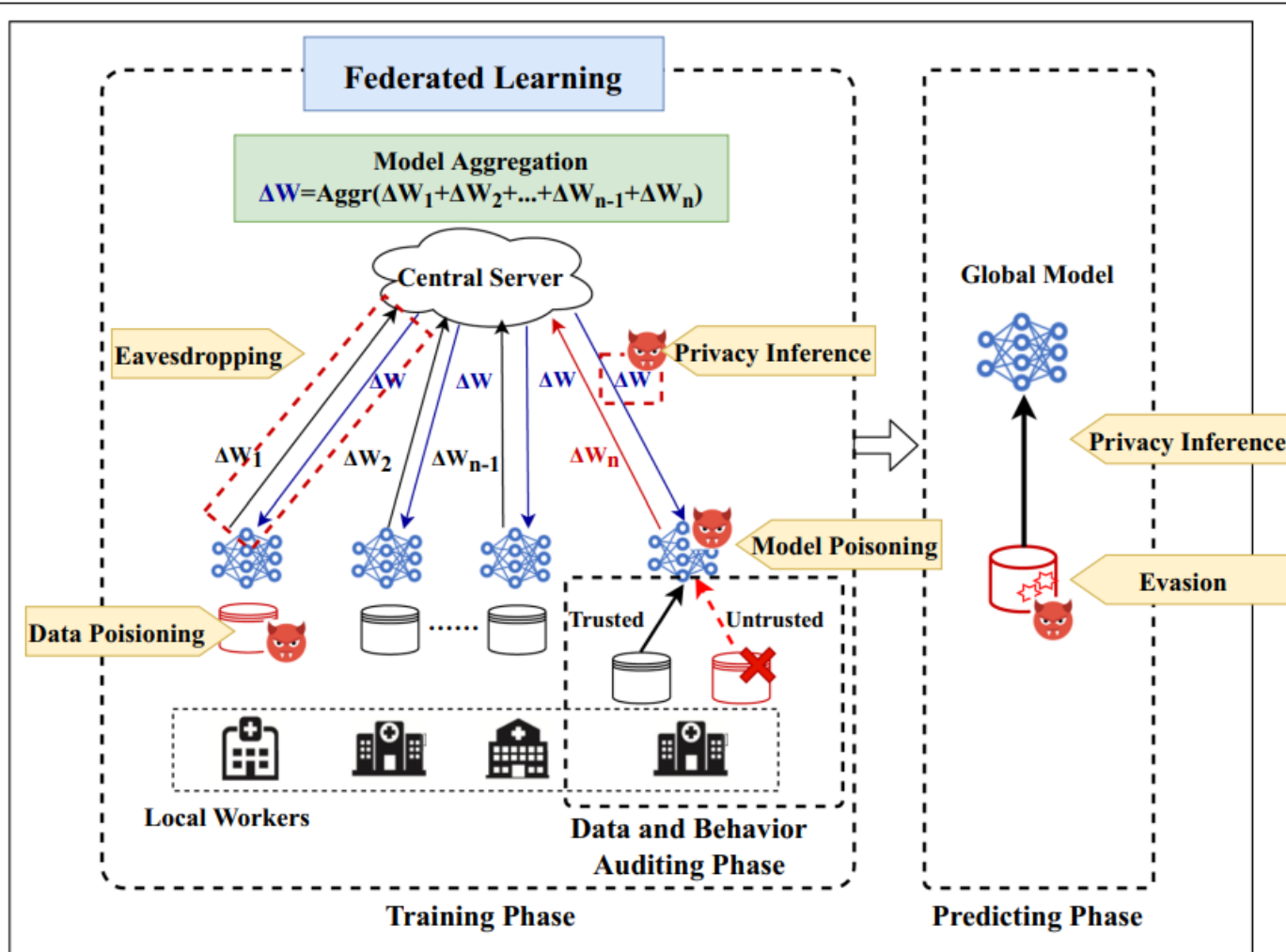
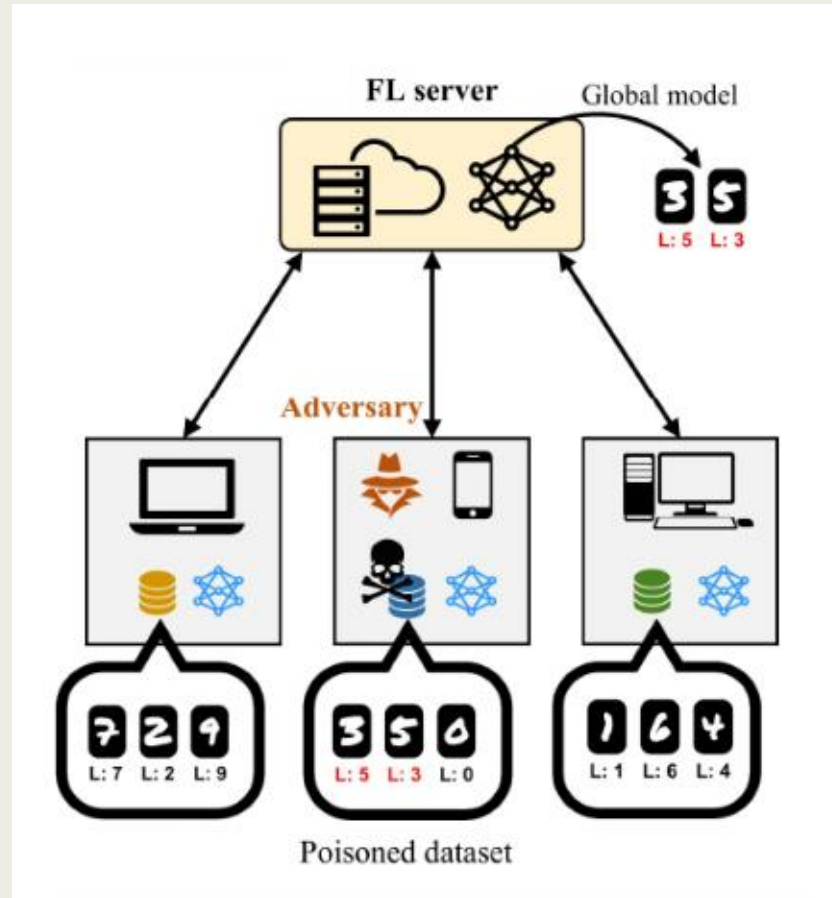


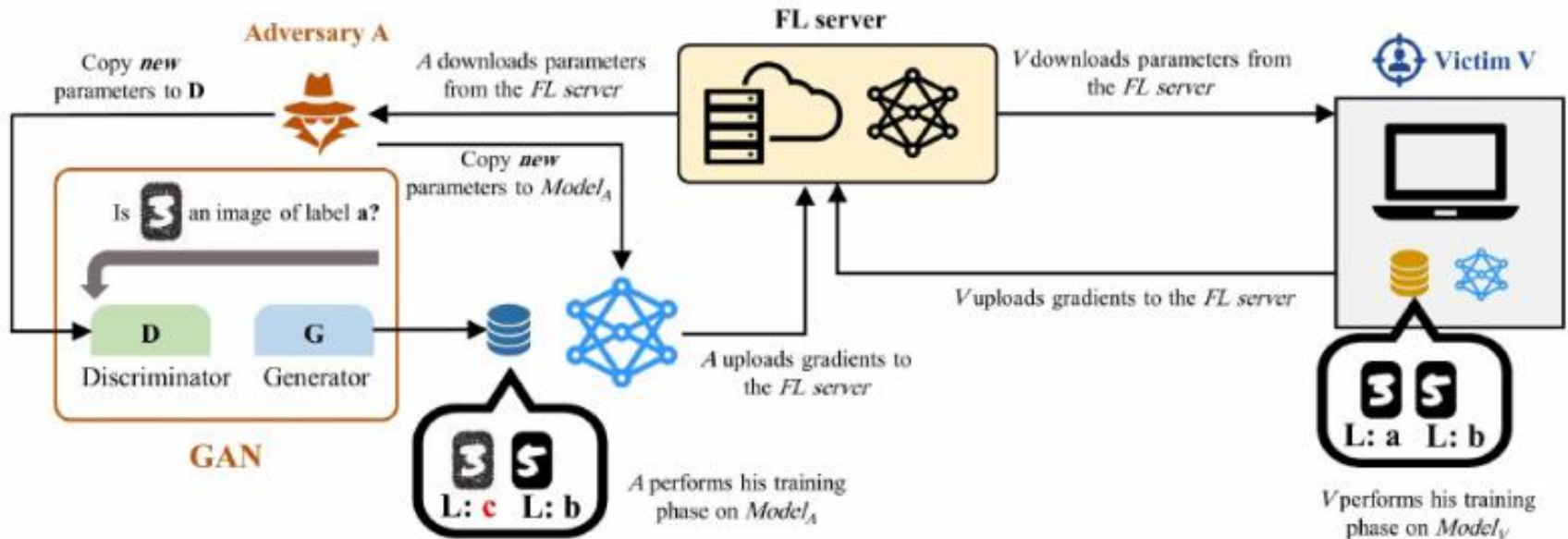
Fig. 1 The multi-phases framework of FL including data and behavior auditing, model training and model predicting

# Data Poisoning Attack in Federated Learning Systems



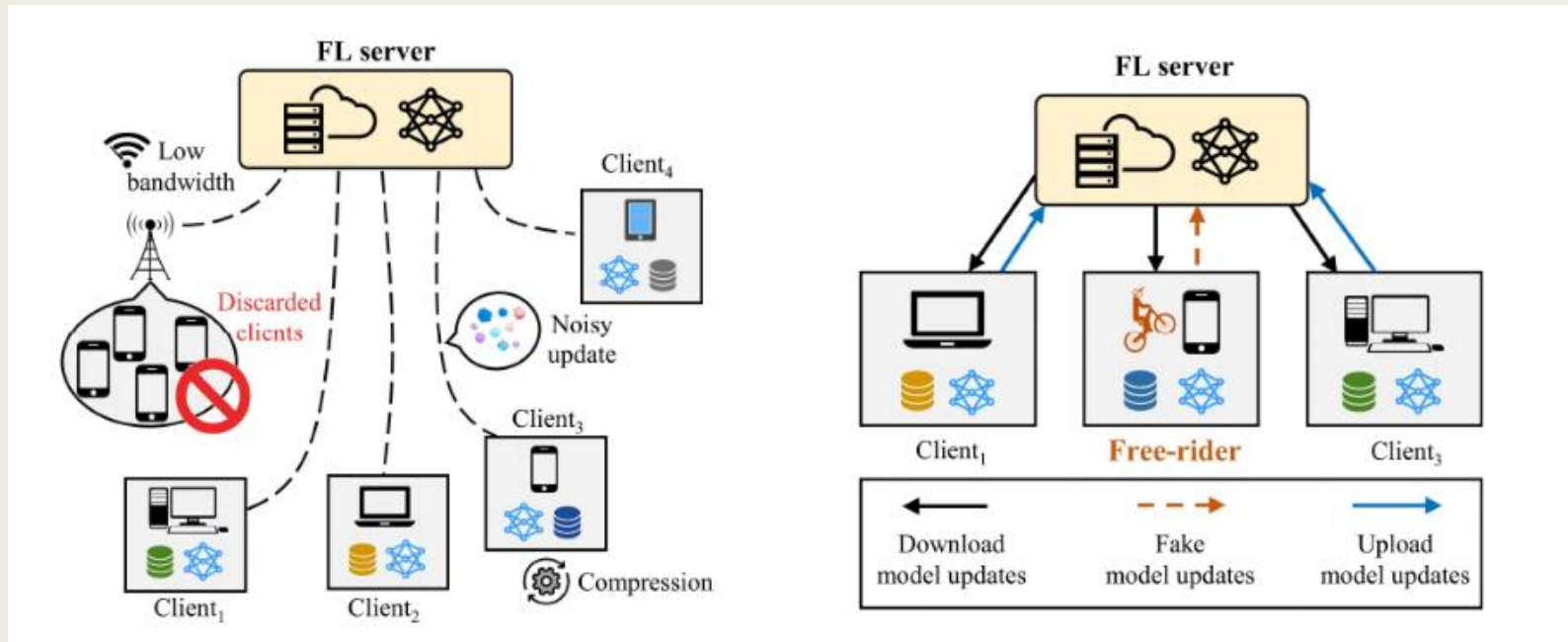


# An Example of GANs-based Inference Attack in FL Systems



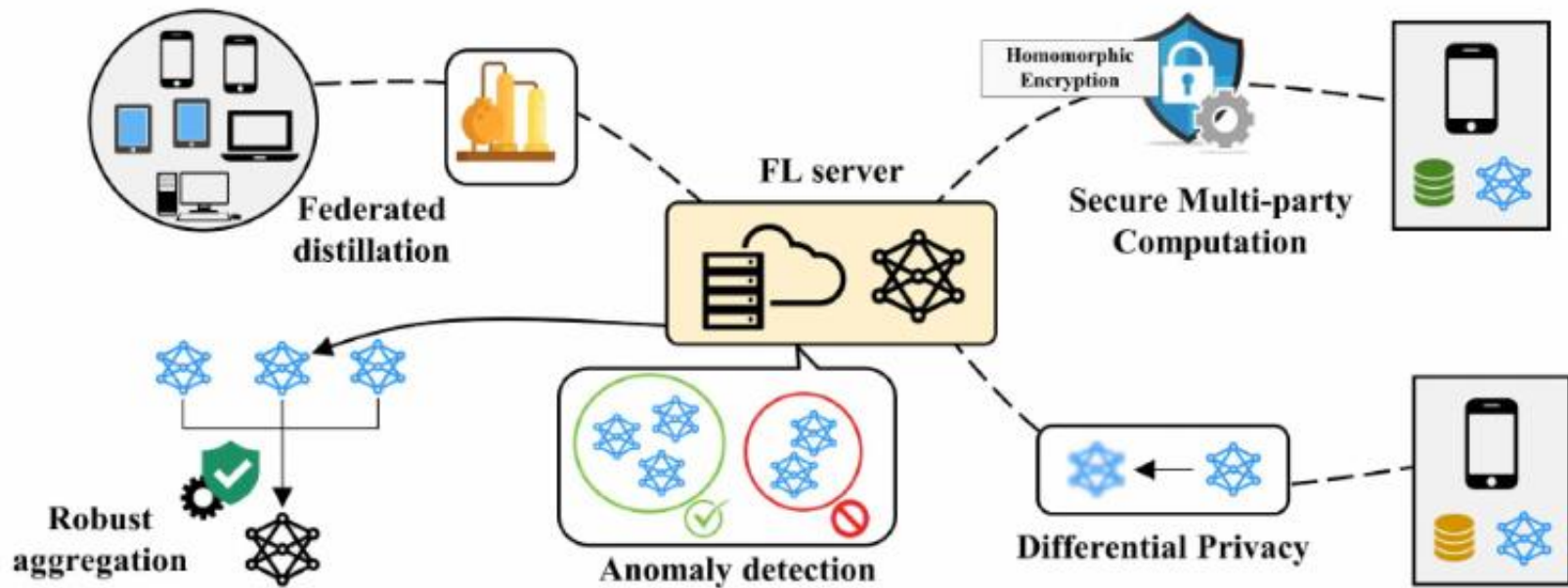
# Federated Learning Systems: Challenges

## Communications bottlenecks in FL systems



An example of free-riding attack in FL systems

# An Overview of Defensive Mechanisms in FL Systems

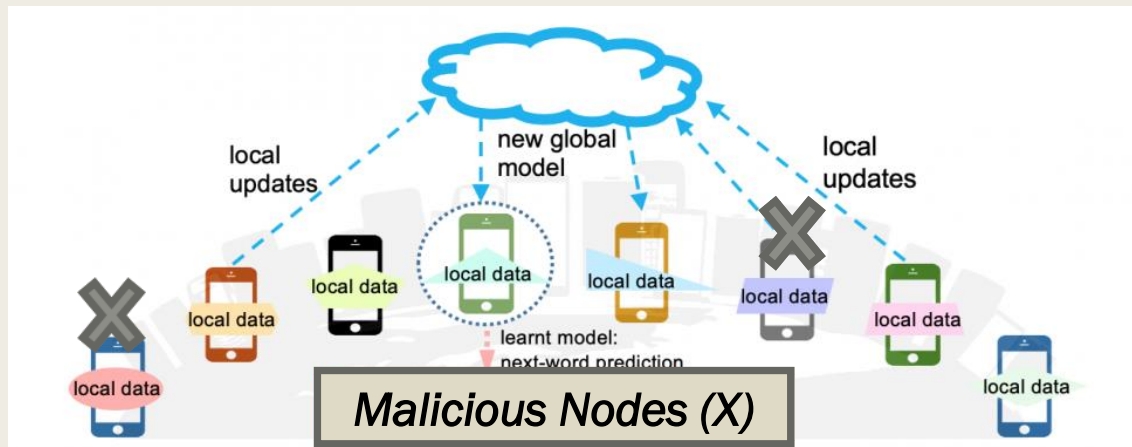


# Federated Learning Defensive Mechanisms

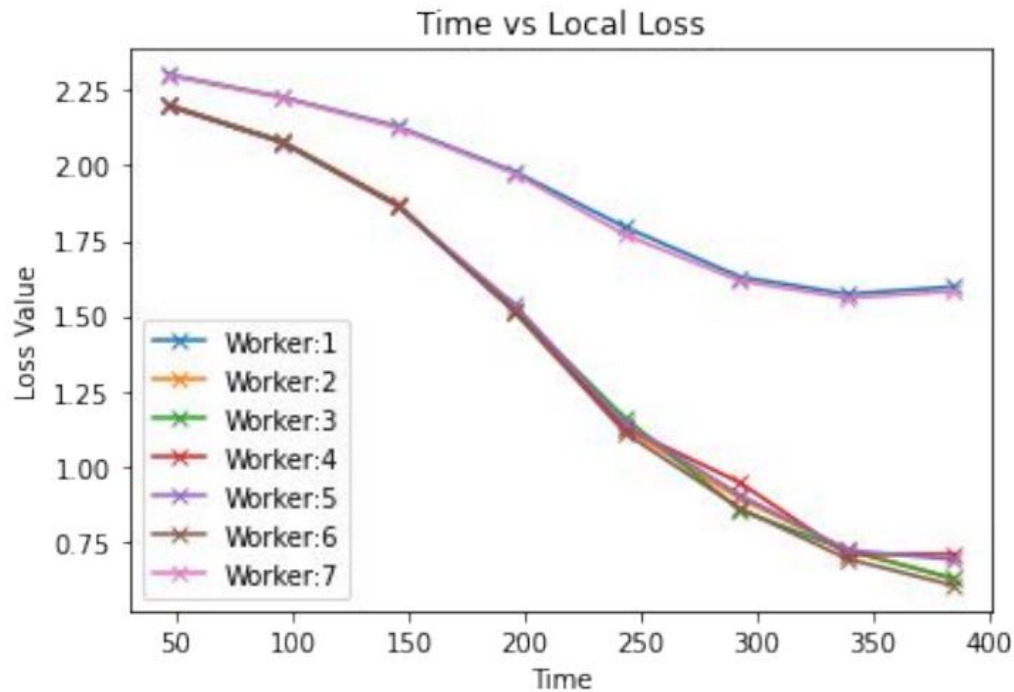
Defensive mechanisms	Key idea	Attacks
Differential Privacy	Introduce noise to the client's sensitive data before sharing individual updates with the FL server	<ul style="list-style-type: none"><li>• Data poisoning attacks</li><li>• Backdoor attacks</li><li>• Inference attacks</li></ul>
Secure Multi-party Computation	Encrypt clients' uploaded parameters	<ul style="list-style-type: none"><li>• Inference attacks</li><li>• MITM attacks</li></ul>
Anomaly detection	Analyze clients' updates to identify misbehaving clients	<ul style="list-style-type: none"><li>• Free-riding attacks</li><li>• Model poisoning attacks</li><li>• Data poisoning attacks</li></ul>
Robust aggregation	Detect malicious individual updates during training process	<ul style="list-style-type: none"><li>• Inference attacks</li><li>• Model poisoning attacks</li><li>• Data poisoning attacks</li></ul>
Federated distillation	Transfer knowledge from a fully trained model to another model	<ul style="list-style-type: none"><li>• Communications bottlenecks</li><li>• MITM attacks</li><li>• Inference attacks</li><li>• GANs-based attacks</li></ul>

# Maliciousness in Worker Nodes

- How do we detect Maliciousness in Worker Nodes and incorporate the same in selection criteria?
- Malicious Nodes Definition
  - *e.g.: Nodes with wrongly labelled data*
- The extent of the malicious nodes could be varied
- The number of malicious nodes and the total number of nodes could be varied
- We can also test in a dynamic setting where the nodes may be initially benign and may start turning malicious after some interval of time
- Ignoring such nodes becomes quite important for the selection algorithm



# Incorporating Maliciousness in Worker Nodes: Swap the Labels



## Local Model Loss for Malicious Node Detection

*Total Worker Nodes: 20*

*Malicious Nodes: 4 (Labels swapped)*

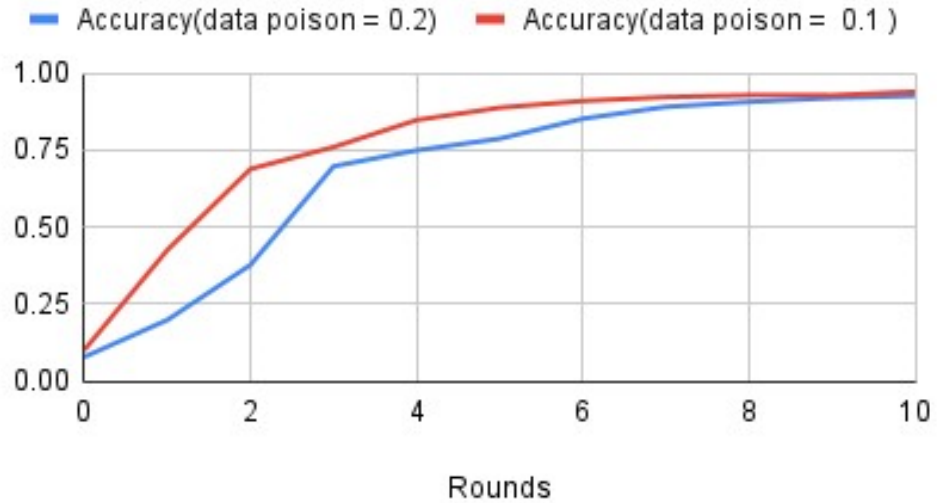
*Data Distribution: Homogeneous*

*Dataset: MNIST*

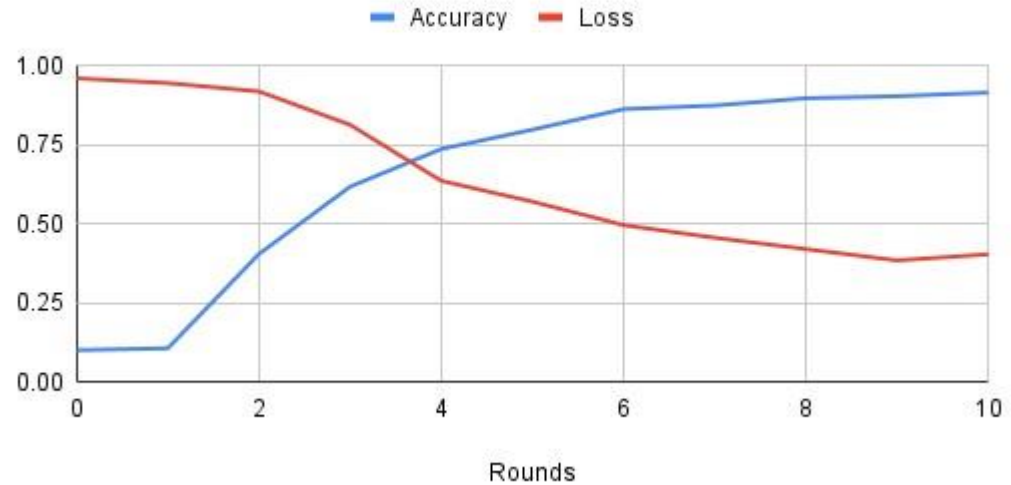
Considerably higher local model loss values for malicious nodes

# Data Poisoning Attacks

Accuracy(data poison = 0.2) and Accuracy(data poison = 0.1)

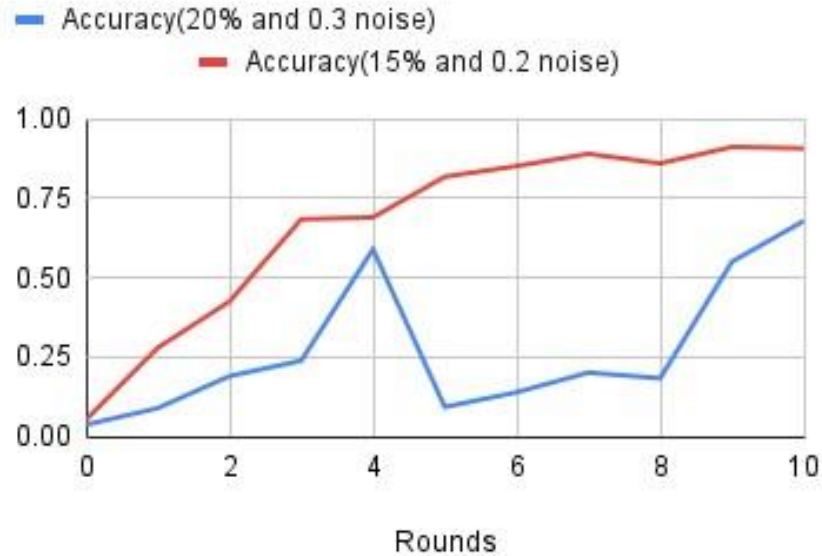


Accuracy and Loss (Data Poison rate : 0.4)

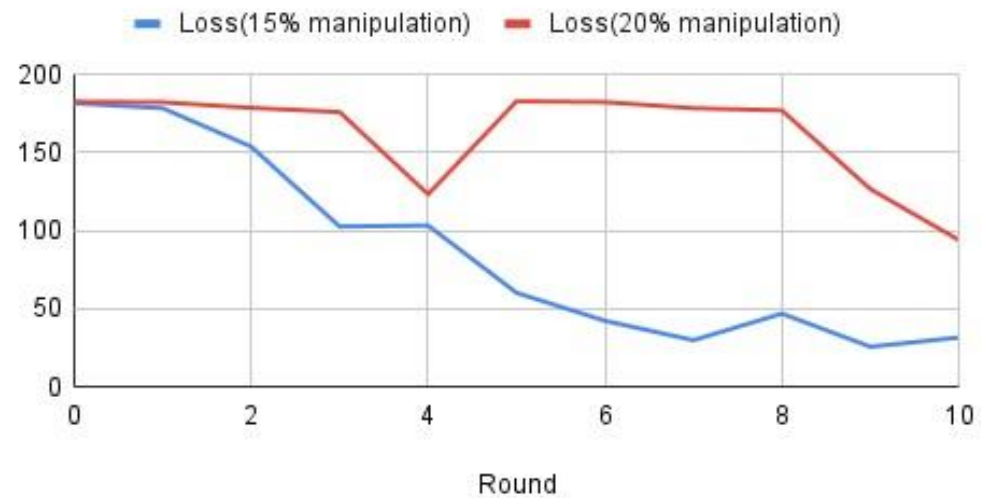


# Gradient Poisoning Attacks

## Accuracy at different noise rates



## Loss(15% manipulation) and Loss(20%)





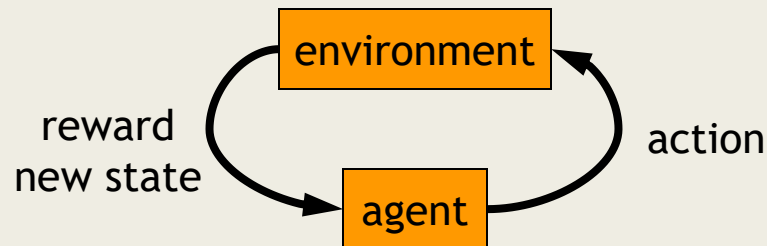
# EMERGING PARADIGMS AT THE EDGE

## *REINFORCEMENT LEARNING*

Work in Progress

# Fundamentals

- Supervised learning
  - *classification, regression*
- Unsupervised learning
  - *clustering*
- Reinforcement learning
  - *more general than supervised/unsupervised learning*
  - *learn from interaction w/ environment to achieve a goal*



# New Challenges in Reinforcement Learning: A Survey of Security and Privacy

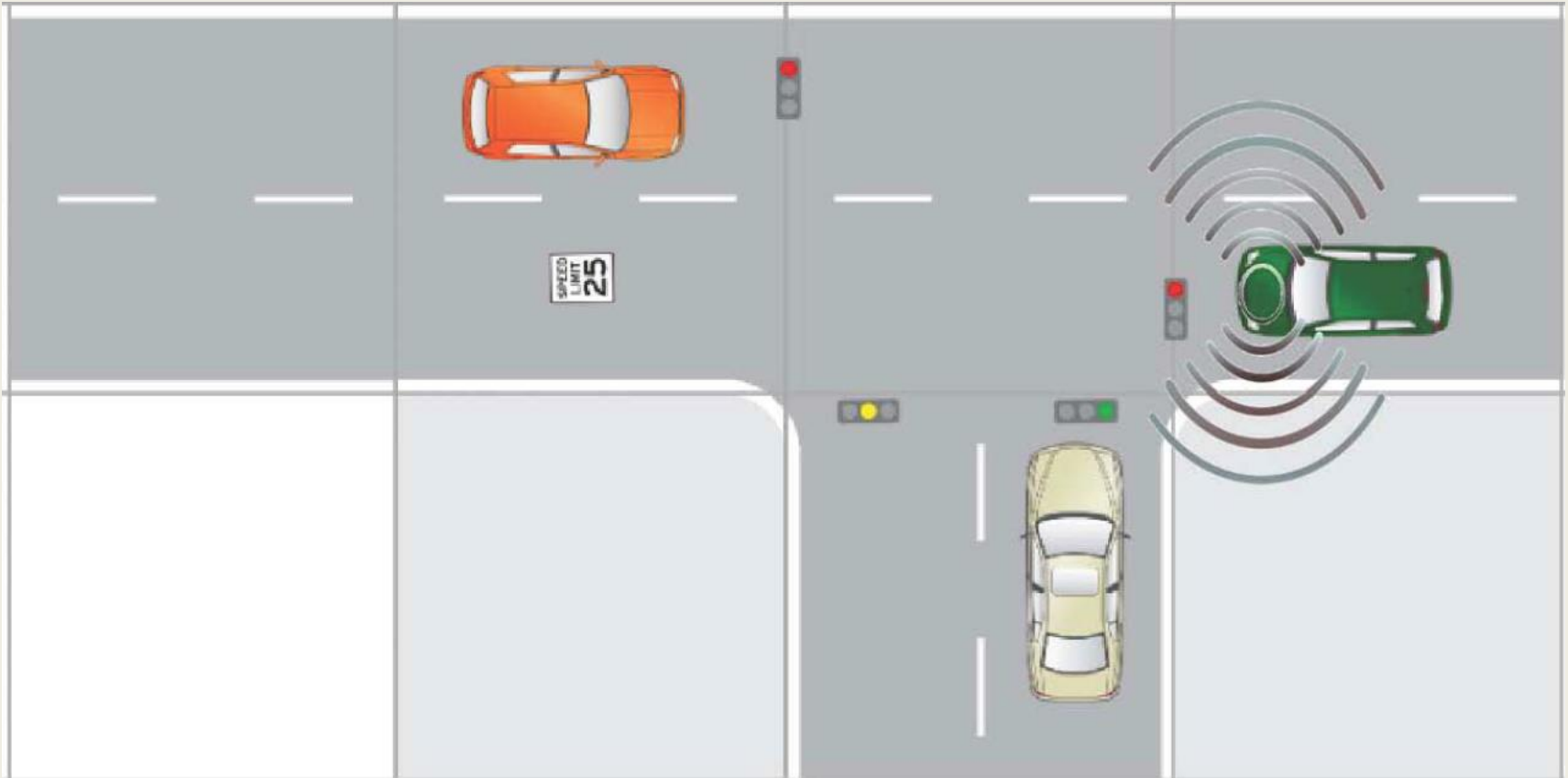
Yunjiao Lei<sup>1</sup>, Dayong Ye<sup>1</sup>, Sheng Shen<sup>1</sup>, Yulei Sui<sup>1</sup>, Tianqing  
Zhu<sup>1\*</sup> and Wanlei Zhou<sup>2</sup>

<sup>1\*</sup>School of Computer Science, University of Technology Sydney,  
Broadway, Sydney, 2007, NSW, Australia.

<sup>2\*</sup>School of Data Science, City University of Macau, Macau,  
China.

Springer Nature 2021

# An Autonomous Driving Scenario



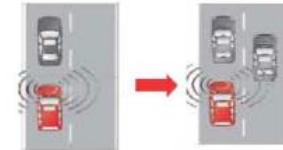
*The green car is an agent. the environment comprises the road, the trac signs, other cars, etc.*

# A Simple Example of a Security Attack in Reinforcement Learning in the Context of Automatic Driving

Action attack: Tempting the agent to take an action of "turn right", rather than the optimal action of "go straight".



Environment Attack: Changing the road condition to mislead the agent to take a wrong action.



Reward attack: Giving a wrong reward of +1, instead of -1.



# Summary of Research Addressing Security in Reinforcement Learning

Subsection	Papers	Target	Impact	Strategies	Representative Methods
Security of state and action in MDP	Lee et al. [58]	Action	Reward	Perturbations	Optimization-based approaches Projected gradient descent
	Chen et al. [56]	Action	Policy	Action robustness	Zero-sum game Nash equilibrium
	Zhao et al. [45]	State	Policy Action	Perturbations	Imitation learning
	Garrett et al. [64]	State	System destabilization	Perturbations	Z tables
	Sun et al. [40]	State	Reward, Action	Perturbations	Prediction model Neural network
	Ye et al. [57]	State	Action	Model learning	Deep neural network Convolutional neural network
	Dai et al. [65]	State-action	Policy	Safe exploration	Transfer learning
Security of environment in MDP	Rakhsha et al. [43]	Transition dynamics / rewards	Policy	Data poisoning	Optimization problems having constraints
	Chan et al. [59]	Features	Reward	Adversarial sample	Sliding-window method Gradient function Cross-entropy method
	Wang et al. [22]	Environment conditions	Robust policy	Robust adversarial learning	Actor-critic architecture Minimax optimization
	Li et al. [46]	Non-stationary environment	Robust policies	Robust adversarial learning	End-to-end learning approach
	Lin et al. [44]	Features	Action	Adversarial sample	Gradient-based methods
	Li et al. [66]	Environment	Policy	Two-player zero-sum game	Nash equilibrium
	Zhai et al. [67]	Environment	Policy	Two-player zero-sum game	Nash equilibrium Lyapunov network
Security of reward function in MDP	Zhang et al. [54]	Reward	Policy	Poisoning attack	Optimal control problems
	Li et al. [68]	Reward	Policy	Adversarial inverse reinforcement learning	Imitation learning Entropy regularization term

# Key Findings of the Edge Security Report

- Edge deployments are increasing in scale across investments, projects, use cases, endpoints and types of endpoints
- Security is the top challenge cited by enterprises with edge deployments
- Risks to edge systems such as cyberattacks and from edge systems due to vulnerabilities and misconfigurations are on the rise

Reference:

<https://www.redhat.com/en/resources/state-of-edge-security-report-overview>

# Summary and Future Directions

- MEC Security is a critical area that needs a lot more attention considering the huge growth of the Edge
- New paradigms at the Edge such as Federated Learning, Reinforcement Learning, etc are likely to spawn additional attack surfaces and attack vectors
- Need robust mitigation of the attacks since Edge nodes will become more complex with each passing year



THANK YOU

[rajeevshorey@gmail.com](mailto:rajeevshorey@gmail.com)