



# Blockchain-based Federated Learning: privacy and incentive

## ECE6903J - Distributed Machine Learning Systems (Research project)

Hugo Vanhille, Pedro Hernández Rubio

Department of Automation

2022 年 12 月

# 目录

## 1 Background

- Motivation
- Crowdsensing

## 2 Research

- Problems
- The privacy-preserving of Federated Learning
- The incentive mechanism of Federated Learning

## 3 System architecture

Software application

## 4 Security issues: privacy

- Provenance of data
- Data privacy

## 5 Quality management: incentive

- Incentive mechanism
- Mechanism design: multifactor
- Mechanism design: issues

## 6 Conclusions

- Application
- Limitations



## 第 1 节

# Background



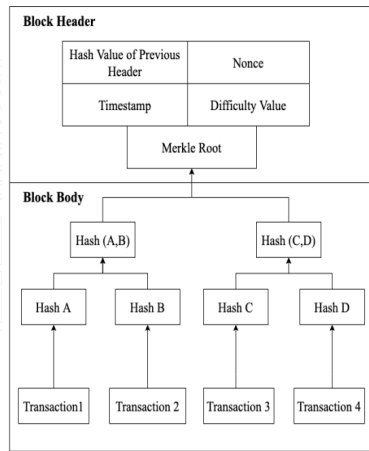
# Motivation

- Research interest mainly targeted to **blockchain technology** (its application to distributed Machine Learning systems)
- Specifically, applied to data-aggregation systems (e.g. **crowdsensing** in the Internet of Things (IoT) field)
- Could similar approach be applied for **Federated Learning**?



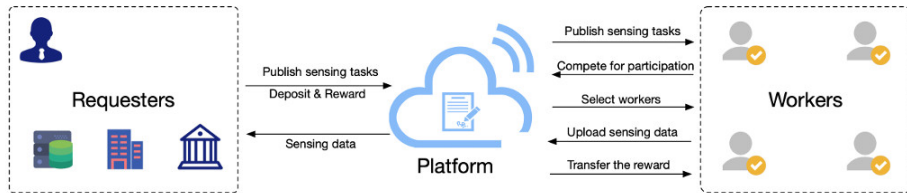
# Blockchain technology

Distributed ledger containing a time-stamped series of immutable blockchains, trustless, decentralized, proof-tampering and full traceability



# Crowdsensing: definition

- **Crowdsensing:** emerging paradigm of data aggregation, having a key role in data-driven applications. Specially used for getting large amounts of IoT sensing data, by using the individual intelligent sensing devices.
- **Benefit:** improved data collection efficiency and reduced costs effectively



# Crowdsensing issues: security

- 1 Managed and maintained **centralized platforms** suffer from the single point of failure

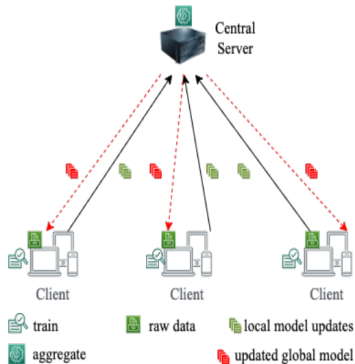


图: Topology of traditional FL



# Crowdsensing issues: incentive

- 1 Encouraging workers by offering appropriate **incentive mechanisms** (monetary usually) → auction theory guarantees benefits for both requesters and workers but only provide short-term incentives



图: Monetary reward



图: Worker reputation



图: Data quality





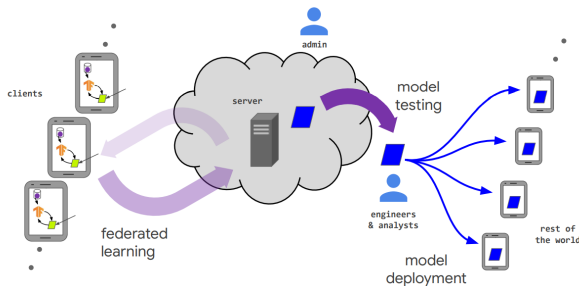
## 第 2 节

## Research



# The privacy-preserving of Federated Learning

- FL provides an attractive structure for decomposing the overall machine learning workflow into the approachable modular units we desire.
- FL provides a level of privacy to participating users through data minimization.



# The incentive mechanism of Federated Learning

- Main types of incentive mechanisms:
  - ① **Monetary-based**: distributing rewards.
  - ② **Reputation-based**: reputation framework for worker selection (algorithms)
- **Limitations**
  - ① Relies on a central platform, vulnerable to target attacks
  - ② Single-attribute incentive mechanisms (multifactor incentive needed)

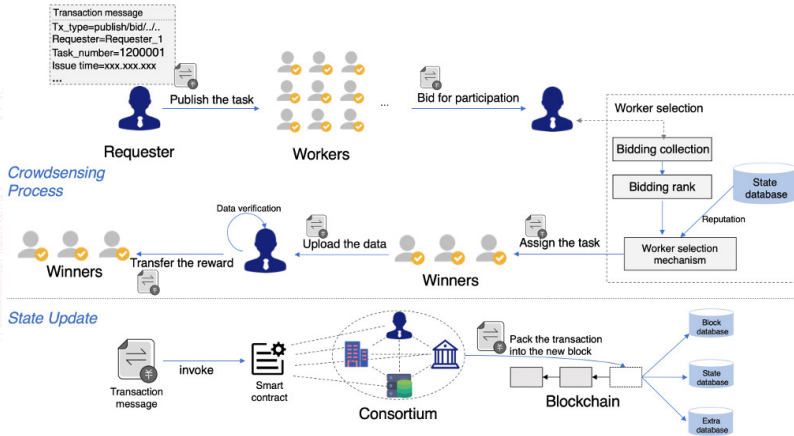


## 第 3 节

# System architecture



# System architecture



## 第 4 节

# Security issues: privacy

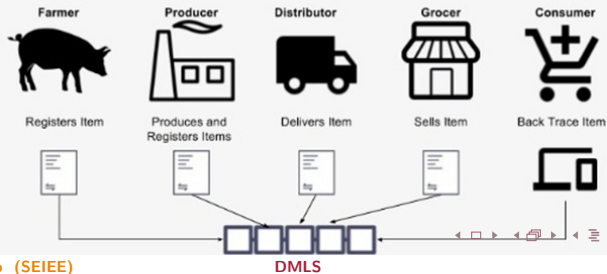


# Provenance of data

## Model updates

A blockchain-based privacy-preserving federated learning framework leverages the immutability and decentralized trust properties of blockchain to provide the **provenance of model updates** (smart contracts)

### Example: Global Food Supply Chain



# Data privacy

## Improving data privacy in FL scenario:

- **Storing evidence:** by using hashing and fingerprint mechanisms, references can be stored proving both local data and models are correct
- **Limiting access:** by making the ledger network only accessible via private network of participants
- **Zero Knowledge Proofs:** advanced (and computationally expensive) cryptographical techniques for granular information disclosure (both for mutual verification and partial data disclosure)





## 第 5 节

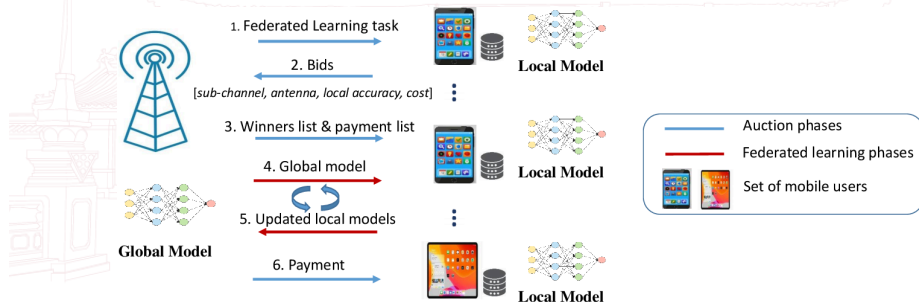
# Quality management: incentive



# Incentive mechanism

## Federated Learning scenario

An effective incentive mechanism combining reputation with contract theory motivates high-reputation mobile devices with high-quality data to participate in model learning



# Mechanism design: multifactor

- Based on three parameters:
  - ① Workers' bidding
  - ② Reputation
  - ③ Recent data quality estimation
- Analytic Hierarchy Process (AHP) framework → (top-down)
  - ① Objective level: winning workers
  - ② Criteria level: parameters criteria
  - ③ Alternative level: workers available

## Multifactor worker evaluation approach

$$\theta_i = \omega_1 B_i + \omega_2 R_i + \omega_3 Q_i \quad \text{where } \omega_i \geq 0 \text{ and } \sum_{i=1}^3 \omega_i = 1$$



# Mechanism design: issues

## ① How to select appropriate workers?

- **Proposal:** decentralized architecture (blockchain technology) that lacks a single point of failure, and enhances privacy with asymmetric encryption and digital signature technology

## ② How to distribute the rewards to the workers?

With the help of **mechanism design theory** two important properties for the incentive mechanism are guaranteed:

- **Incentive quality (IC):** the truthful submission of training cost is the worker's optimal bidding strategy
- **Individual rationality (IR):** the reward must compensate for the worker's cost (non-negative)



## 第 6 节

# Conclusions



# Results

- **Benefits of consortium blockchain technology:**
  - resistant to the single point of failure (system security)
  - more transparency (trusting data provenance)
  - privacy-preserving (e.g. ZKP)
  - cooperative management (by requesters) reduces cost and enhances the flexibility of the system (selection criteria)
- **Benefits of hybrid incentive mechanism:**
  - encourages workers to contribute valuable data (and penalizes malicious ones)
  - ensures favorable short-term and long-term incentives for workers



# Limitations

Further research:

- ① Dynamic situation where evaluations attributes are changing
- ② Optimization of consensus protocol (better performance)
- ③ Further protection of worker privacy





谢谢