FL Platforms

2022_Fall

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FL Platforms

Open FL Platform (Active), https://github.com/Kwangkee/FL/blob/main/FL@Platform.md#open-fl-platform-active

Open FL Platform (Etc), https://github.com/Kwangkee/FL/blob/main/FL@Platform.md#open-fl-platform-etc

FL Benchmark, https://github.com/Kwangkee/FL/blob/main/FL@Platform.md#fl-benchmark

Commercial FL Platform, https://github.com/Kwangkee/FL/blob/main/FL@Platform.md#commercial-fl-platform

FLRA: A Reference Architecture for Federated Learning Systems

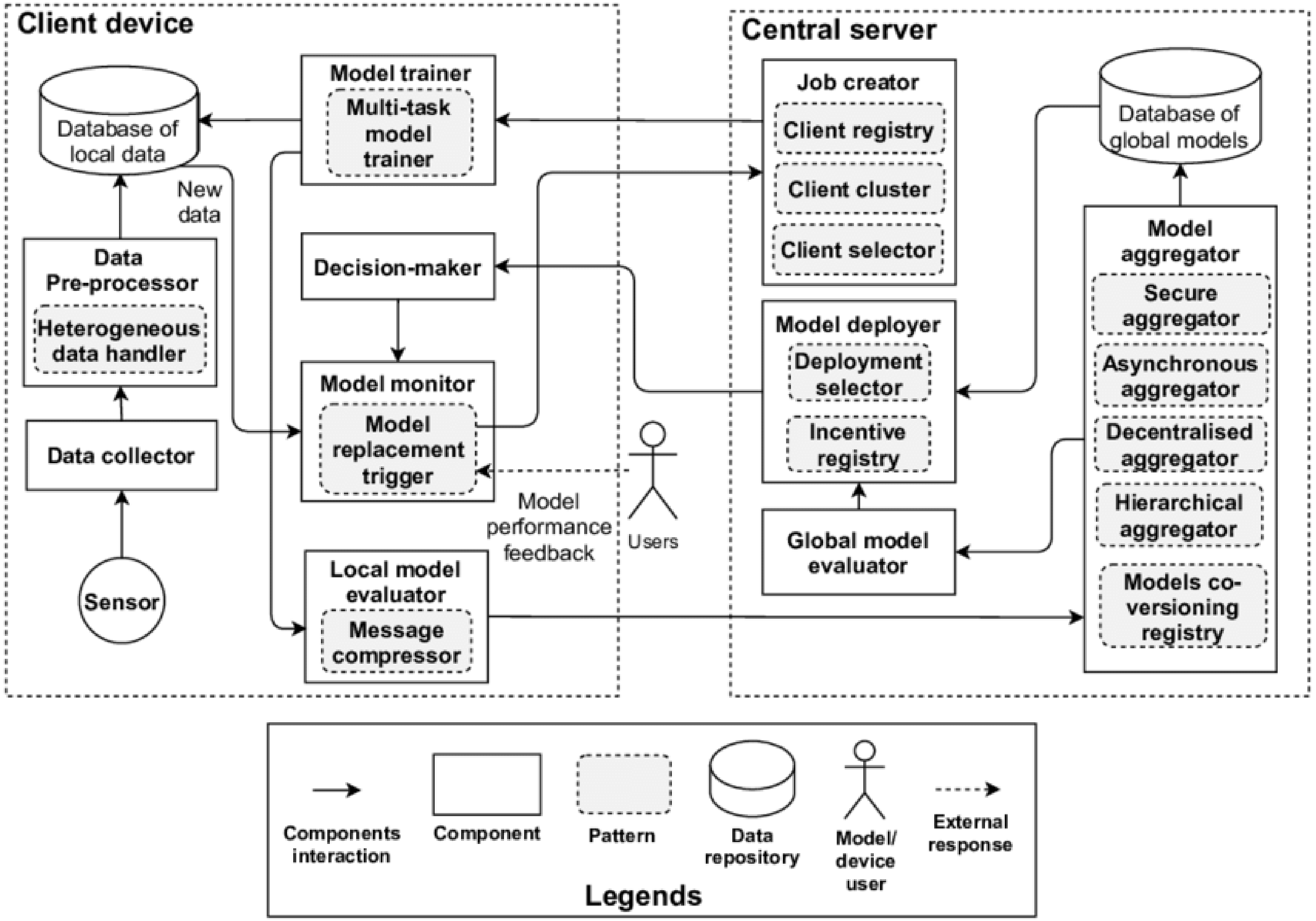
FLRA: A Reference Architecture for Federated Learning Systems, https://arxiv.org/abs/2106.11570

Although much effort has been put into federated learning from the machine learning perspectives, our previous systematic literature review on the area shows that there is a distinct lack of considerations for software architecture design for federated learning. In this paper, we propose FLRA, a reference architecture for federated learning systems, which provides a template design for federated learning-based solutions.

The FLRA reference architecture consists of a pool of architectural patterns that could address the frequently recurring design problems in federated learning architectures. The FLRA reference architecture can serve as a design guideline to assist architects and developers with practical solutions for their problems, which can be further customised.

FLRA: A Reference Architecture for Federated Learning Systems

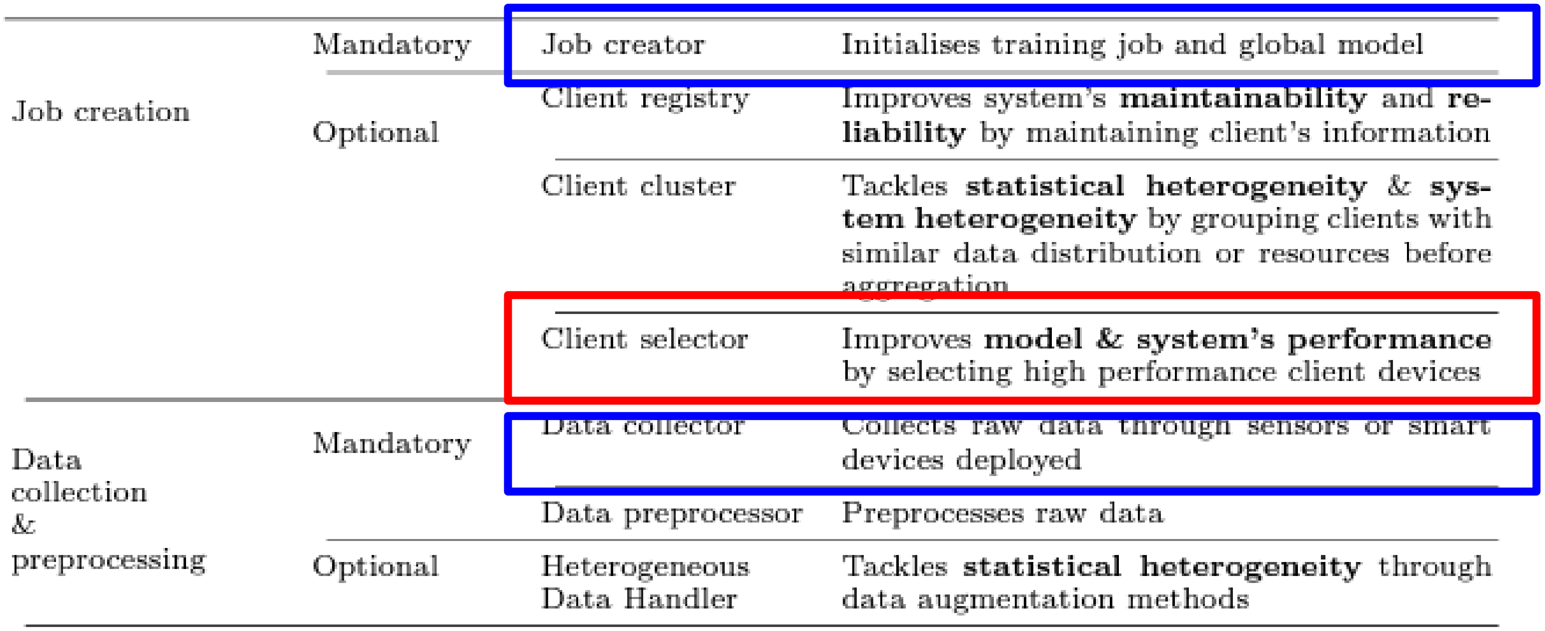
FLRA: A Reference Architecture for Federated Learning Systems, https://arxiv.org/abs/2106.11570



FLRA: A Reference Architecture for Federated Learning Systems

FLRA: A Reference Architecture for Federated Learning Systems, https://arxiv.org/abs/2106.11570

The central servers interacts with a massive number of client devices that are both system heterogeneous and statistically heterogeneous. The magnitude of client devices number is also several times larger than that of the distributed machine learning systems [18,24]. To increase the model and system performance, client devices can be selected every round with predefined criteria (e.g., resource, data, or performance) via client selector component.



Job creation	Mandatory	Job creator	Initialises training job and global model
	Optional	Client registry	Improves system's **maintainability** and **reliability** by maintaining client's information
		Client cluster	Tackles **statistical heterogeneity** & **system heterogeneity** by grouping clients with similar data distribution or resources before aggregation
		Client selector	Improves **model & system's performance** by selecting high performance client devices
Data collection & preprocessing	Mandatory	Data collector	Collects raw data through sensors or smart devices deployed
		Data preprocessor	Preprocesses raw data
	Optional	Heterogeneous Data Handler	Tackles **statistical heterogeneity** through data augmentation methods

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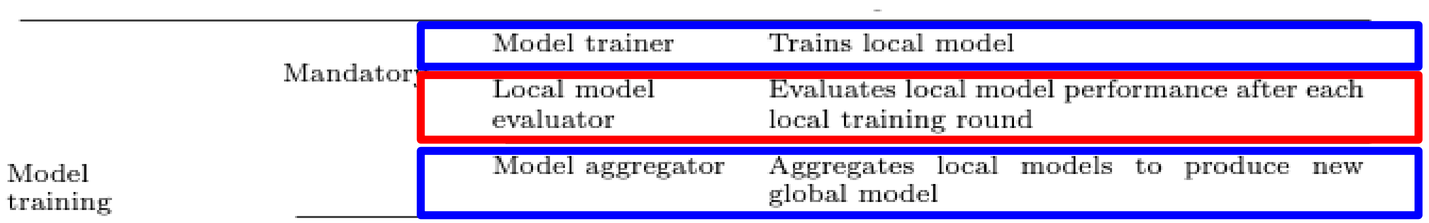
Local model training.
Once the client receives the job from the central server, the model trainer component performs model training based on configured hyperparameters (number of epochs, learning rate, etc.). In the standard federated learning training process proposed by McMahan in [28], only model parameters (i.e., weight/gradient) are mentioned to be sent from the central server, whereas in this reference architecture, the models include not only the model parameters but also the hyperparameters.

Model evaluation.
The local model evaluator component measures the performance of the local model and uploads the model to the model aggregator on the central server if the performance requirement is met. In distributed machine learning systems, the performance evaluation on client devices is not conducted locally, and only the aggregated server model is evaluated. However, for federated learning systems, local model performance evaluation is required for system operations such as client selection, model co-versioning, contributions calculation, incentive provision, client clustering, etc.



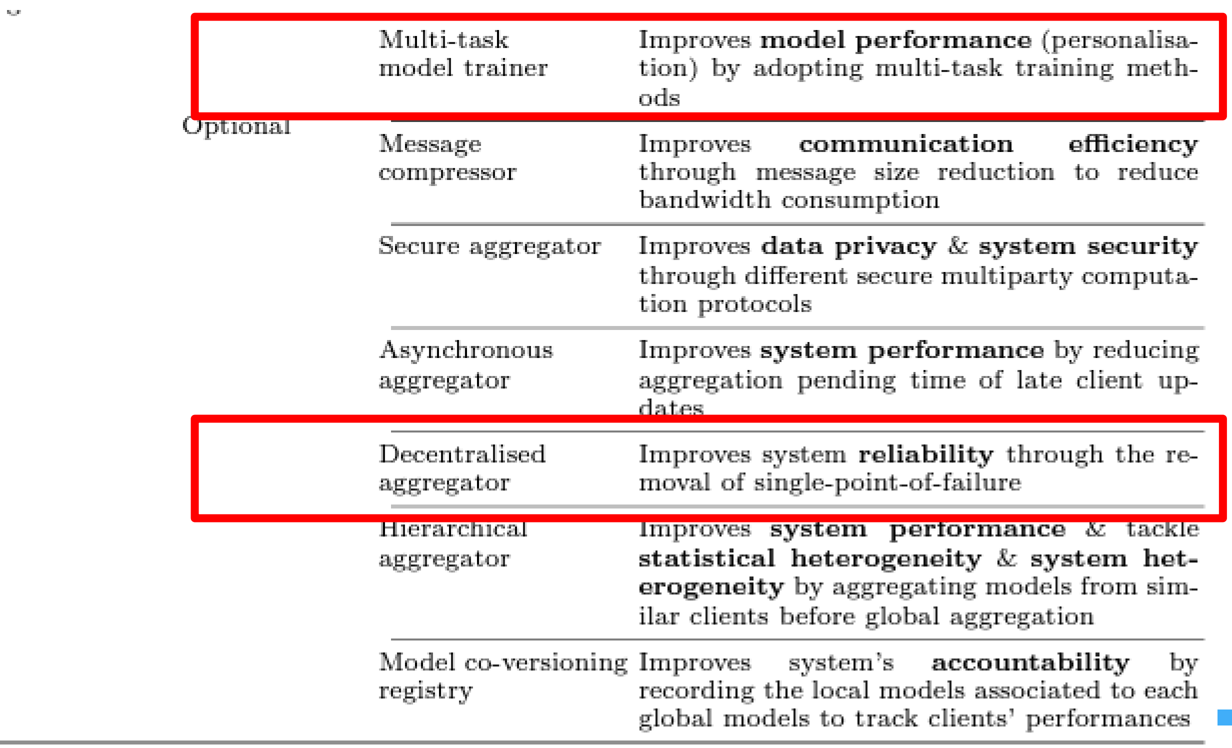
Model training	Mandatory	Model trainer	Trains local model
		Local model evaluator	Evaluates local model performance after each local training round
		Model aggregator	Aggregates local models to produce new global model

FLRA: A Reference Architecture for Federated Learning Systems

FLRA: A Reference Architecture for Federated Learning Systems, https://arxiv.org/abs/2106.11570

this technique is particularly relevant when faced with nonIID data which can produce personalised model that may outperform the best possible shared global model [18]

The conventional design of a federated learning system that relies on a central server to orchestrate the learning process might lead to a single point of failure. A decentralise aggregator performs model exchanges and aggregation in decentralised manner to improve system reliability. The known uses of decentralised aggregator include BrainTorrent [31] and FedPGA [15]. Blockchain can be employed as a decentralised solution for federated learning systems.



Optional	Multi-task model trainer	Improves **model performance** (personalisation) by adopting multi-task training methods
	Message compressor	Improves **communication efficiency** through message size reduction to reduce bandwidth consumption
	Secure aggregator	Improves **data privacy** & **system security** through different secure multiparty computation protocols
	Asynchronous aggregator	Improves **system performance** by reducing aggregation pending time of late client updates
	Decentralised aggregator	Improves system **reliability** through the removal of single-point-of-failure
	Hierarchical aggregator	Improves **system performance** & tackle **statistical heterogeneity** & **system heterogeneity** by aggregating models from similar clients before global aggregation
	Model co-versioning registry	Improves system's **accountability** by recording the local models associated to each global models to track clients' performances

FLRA: A Reference Architecture for Federated Learning Systems

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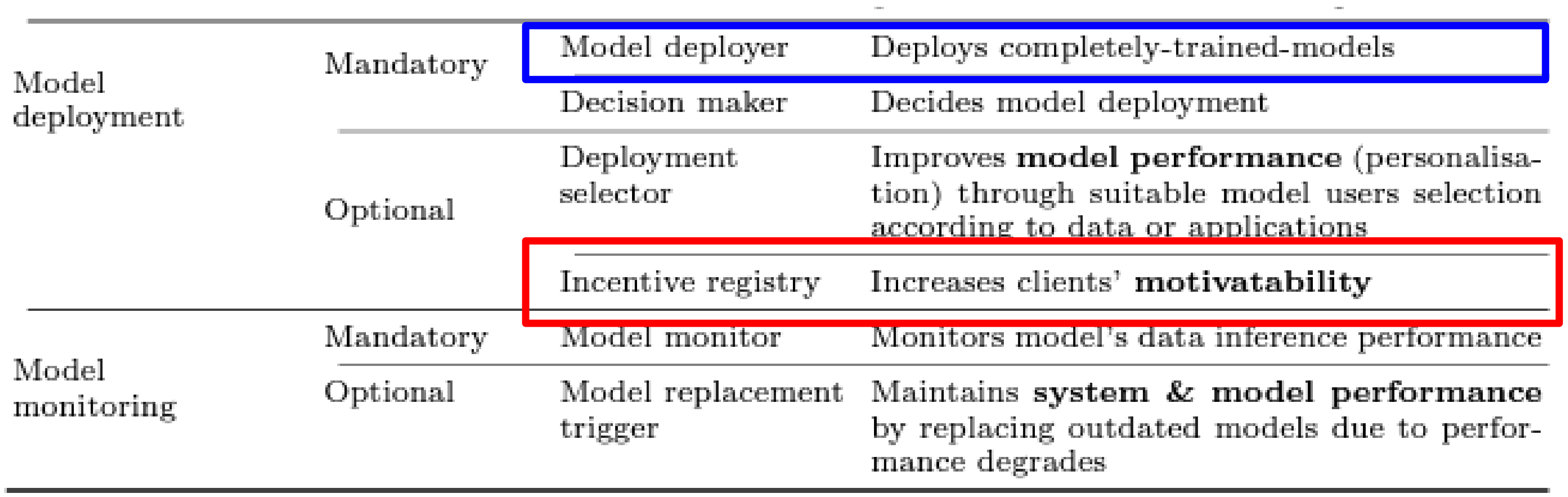
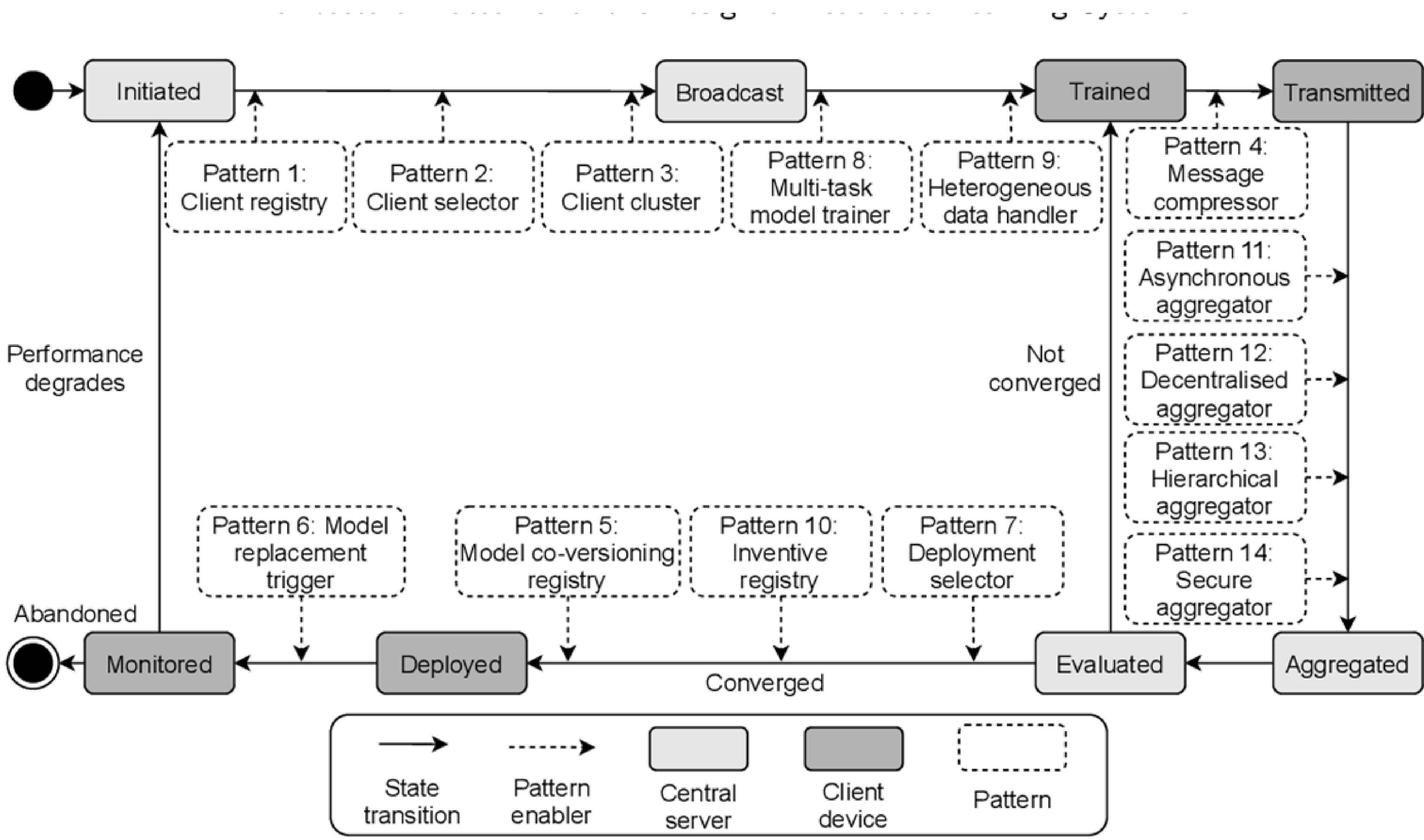
The incentive registry component maintains all the client devices' incentives based on their contributions and agreed rates to motivate clients to contribute to the training. Blockchain has been leveraged in FLChain [3] and DeepChain [36] to build a incentive registry.



Model deployment	Mandatory	Model deployer	Deploys completely-trained-models
		Decision maker	Decides model deployment
	Optional	Deployment selector	Improves **model performance** (personalisation) through suitable model users selection according to data or applications
		Incentive registry	Increases clients' **motivatability**
Model monitoring	Mandatory	Model monitor	Monitors model's data inference performance
	Optional	Model replacement trigger	Maintains **system & model performance** by replacing outdated models due to performance degrades

Architectural patterns for FL

Architectural patterns for the design of federated learning systems, https://arxiv.org/abs/2101.02373



Initiated
Broadcast
Trained
Transmitted
Pattern 1: Client registry
Pattern 2: Client selector
Pattern 3: Client cluster
Pattern 8: Multi-task model trainer
Pattern 9: Heterogeneous data handler
Pattern 4: Message compressor
Pattern 11: Asynchronous aggregator
Pattern 12: Decentralised aggregator
Pattern 13: Hierarchical aggregator
Pattern 14: Secure aggregator
Performance degrades
Not converged
Pattern 6: Model replacement trigger
Pattern 5: Model co-versioning registry
Pattern 10: Inventive registry
Pattern 7: Deployment selector
Abandoned
Monitored
Deployed
Converged
Evaluated
Aggregated
State transition
Pattern enabler
Central server
Client device
Pattern

Blockchain-based trustworthy federated learning architecture

Towards Trustworthy AI: Blockchain-based Architecture Design for Accountability and Fairness of Federated Learning Systems, https://ieeexplore.ieee.org/abstract/document/9686048

https://github.com/Kwangkee/FL/blob/main/FL%40CSIRO.md#towards-trustworthy-ai

- However, federated learning systems struggle to achieve and embody responsible AI principles. In particular, federated learning systems face accountability and fairness challenges due to multi-stakeholder involvement and heterogeneity in client data distribution. To enhance the accountability and fairness of federated learning systems, we present a blockchain-based trustworthy federated learning architecture.
- We designed the architecture based on a reference architecture for federated learning system named FLRA [6]. https://arxiv.org/abs/2106.11570

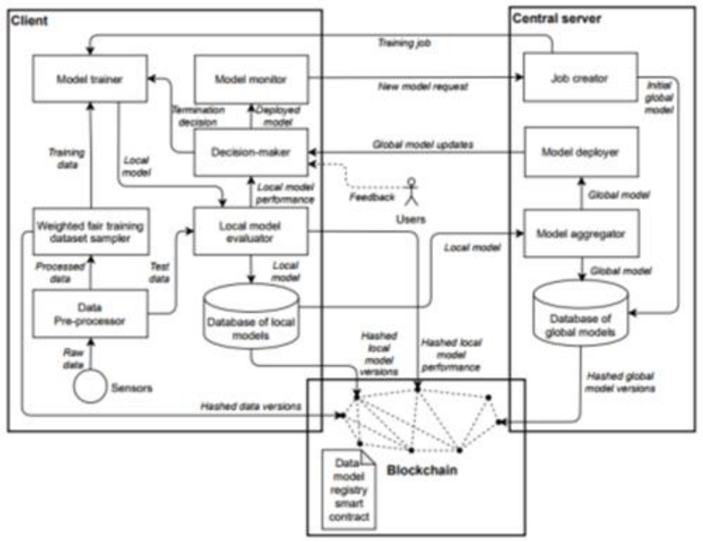


Fig. 1: Blockchain-based Trustworthy Federated Learning Architecture

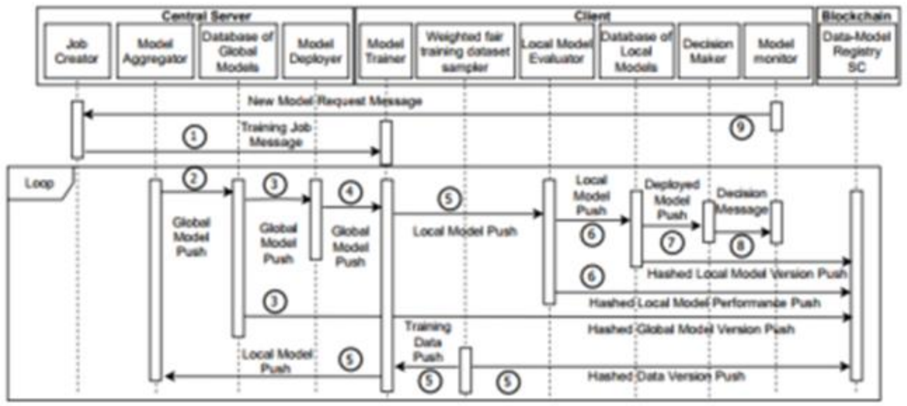


Fig. 2: Sequence Diagram of Blockchain-based Trustworthy Federated Learning Process

BCFL

2CP: Decentralized Protocols to Transparently Evaluate Contributivity in Blockchain Federated Learning Environments, https://arxiv.org/abs/2011.07516

문제정의

- **Cross-device FL** scenario == Crowdsource Setting
  - Initial Model, 검증용 테스트셋 (Validation/Evaluation Dataset) 필요
  - (최소 하나 이상의) Evaluator/Validator/Aggregator 필요
  - 검증 가능한 테스트셋 (highly accurate holdout test set) 과 performance evaluation metric 필요 : Shapley value in FedCoin, contributivity in 2CP, etc.

- **Cross-Silo FL scenario** == Consortium Setting
  - 각 Client가 Training 과 Validation 모두 수행
  - 별도의 Validation Dataset 없는 구조 가능
  - 각 Trainer가 자신의 (학습)데이터로 다른 Trainer의 학습을 Validation/Evaluation

- In the Crowdsource Setting, an organisation or team of researchers wish to produce a machine learning model and decide on a set of model hyperparameters and a training protocol. They do not own enough data to train the model themselves, so must draw on the data from multiple outside sources. – Cross-Devices FL scenario
- In the Consortium Setting, multiple organisations and/or individual data owners wish to combine data to train a model that performs better than any model they could train with only their own data. – Cross-Silos FL scenario

- It follows that we should evaluate datasets retrospectively, rather than before the training process. An ideal way of dividing ownership of a trained model (or its profits) would be to split it according to the value that each participant contributes to the final performance of the model, ie. the contributivity of their data.

Reference: A-2. 블록체인 융합 연합학습 (BCFL)

2CP: Decentralized Protocols to Transparently Evaluate Contributivity in Blockchain Federated Learning Environments, https://arxiv.org/abs/2011.07516

- **Cross-device FL** scenario == Crowdsource Setting
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  - (최소 하나 이상의) Evaluator/Validator/Aggregator 필요
  - 검증 가능한 테스트셋 (highly accurate holdout test set) 과 performance evaluation metric 필요 : Shapley value in FedCoin, contributivity in 2CP, etc.

- For the scenario of the Crowdsource Protocol, we suppose that Alice (the evaluator) has a high quality, well distributed and highly representative dataset for a machine learning task. Her dataset is not large enough to train an effective model for this task, but it is sufficient as a test set to evaluate a trained model.
- Bob, Carol and others (the trainers) own suitable datasets to train Alice's model but they are not willing to share them. They are willing to help Alice train a model using Federated Learning, but want to be fairly rewarded for their contributions. They are, of course, unable to reach consensus on how rewards should be split between them.

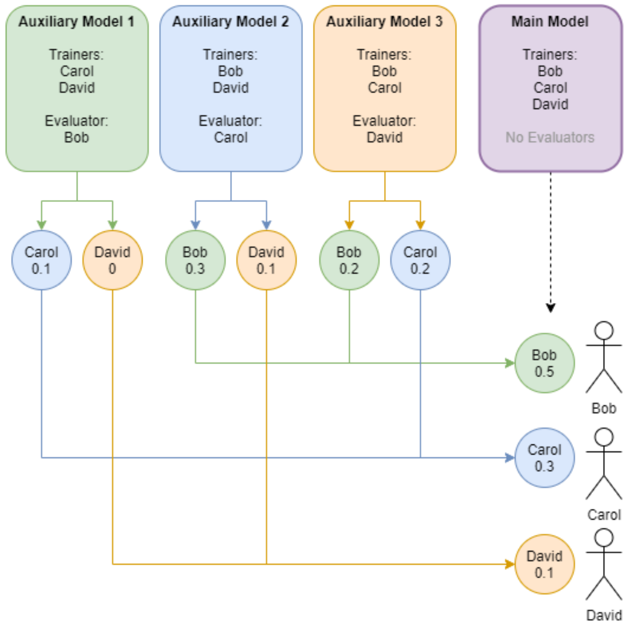
6) The smart contract contains a full history of model updates in each round. Alice can now download all of these and calculate the contributivity of each of them. She assigns a number of tokens to each update on the smart contract, as determined by their contributivity. Each token represents a unit of positive contribution to the model. Note that these tokens do not represent financial value nor affect model governance.

Alice's dataset would be used as the holdout test set. Outside of the Crowdsource setting, such an ideal test set is unlikely to exist, and we cannot use the Crowdsource Protocol.

Reference: A-2. 블록체인 융합 연합학습 (BCFL)

2CP: Decentralized Protocols to Transparently Evaluate Contributivity in Blockchain Federated Learning Environments, https://arxiv.org/abs/2011.07516
Code: https://github.com/cai-harry/2CP

- **Cross-Silo FL scenario** == Consortium Setting
  - 각 Client가 Training 과 Validation 모두 수행
  - 별도의 Validation Dataset 없는 구조 가능
  - 각 Trainer가 자신의 (학습)데이터로 다른 Trainer의 학습을 Validation/Evaluation



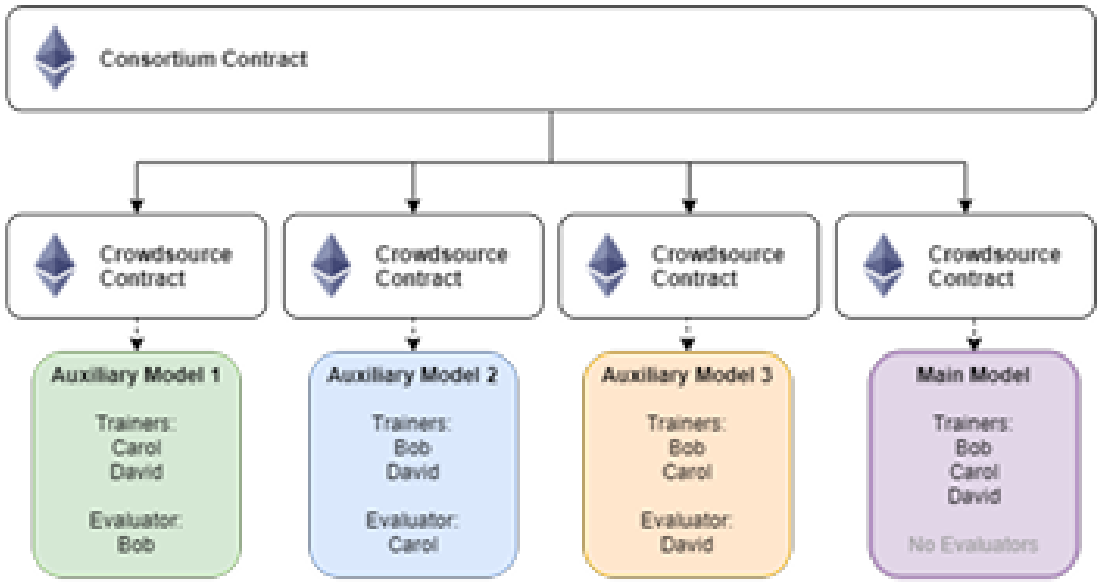


Figure 5. Suppose Alice, Bob and Carol are running the Consortium Protocol. Their Consortium contract orchestrates 4 Crowdsource contracts, which take charge of a model each.

BCFL

2CP: Decentralized Protocols to Transparently Evaluate Contributivity in Blockchain Federated Learning Environments, https://arxiv.org/abs/2011.07516

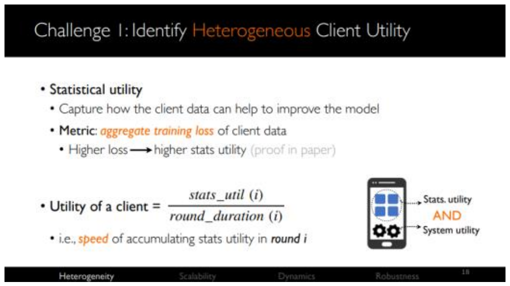
	Cross-device FL	Cross-Silo FL
실증 적용	**D-1. 실증 - DTx , D-2. 실증 - RPM**	**D-3. 실증 - SaMD**
FL scenario	Cross-device FL scenario (>= 1000 lightweight Clients)	Cross-Silo FL scenario (<= 10 Server- level Clients)
In 2CP settings	Crowdsource Setting	Consortium Setting
Stake Holders	- SC Publisher - Aggregator - Evaluator/Validator - Trainer (>= 1000 lightweight Clients)	- SC Publisher - (Optional) Aggregator - Trainer (& Evaluator/Validator) (<= 10 Server-level Clients)
Evaluation/ Validation	- Trainers 와 evaluator/validator 는 서로 다른, 별도로 구분된 역할을 갖음 - Evaluator evaluate the contributions from each Trainers	- 각 Client가 Training 과 Validation 모두 수행 - Each client is responsible for both training and evaluation - Evaluation based on each client's Voting
Validation Dataset	- 검증용/평가용 Validation Dataset 필요 - Evaluator has the validation dataset which is not shared/exposed to the Trainers.	- 별도의 Validation Dataset 없는 구조 가능 - No validation dataset is defined/required - Each Trainer evaluates (other Trainers' contribution) using its own data
Etc.	With Evaluation/Validation, BCFL can support: - Dynamic client/Trainer selection for the next FL round, kicking out bad/lazy guys - Weighted Averaging during Model Parameters aggregation	

Client Selection

Oort: Efficient Federated Learning via Guided Participant Selection, https://www.usenix.org/conference/osdi21/presentation/lai, https://arxiv.org/abs/2010.06081

As a result, data characteristics and device capabilities vary widely across clients. Yet, existing efforts randomly select FL participants, which leads to poor model and system efficiency. In this paper, we propose Oort to improve the performance of federated training and testing with guided participant selection. With an aim to improve time-to-accuracy performance in model training, Oort prioritizes the use of those clients who have both data that offers the greatest utility in improving model accuracy and the capability to run training quickly.

https://github.com/Kwangkee/FL/blob/main/FL@ClientSelection.md
주요 아이디어: loss-based statistical utility design
주요 아이디어: MAB (Multi-Armed Bandit) problem, exploration-exploitation

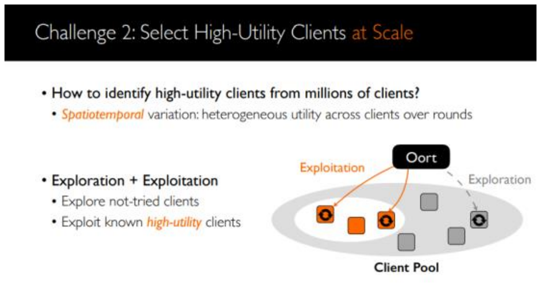


Challenge 1: Identify Heterogeneous Client Utility

- Statistical utility
  - Capture how the client data can help to improve the model
  - Metric: *aggregate training loss* of client data
    - Higher loss $\longrightarrow$ higher stats utility (proof in paper)
- Utility of a client = $\frac{stats\_util\ (i)}{round\_duration\ (i)}$
  - i.e., speed of accumulating stats utility in *round i*

Stats. utility
AND
System utility

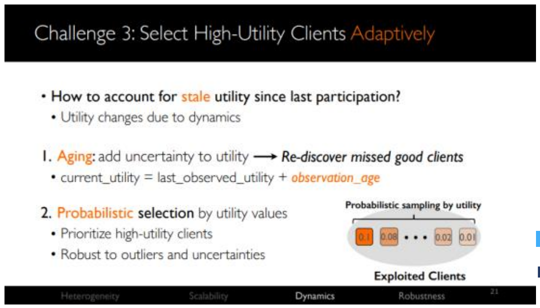
Heterogeneity Scalability Dynamics Robustness 18



Challenge 2: Select High-Utility Clients at Scale

- How to identify high-utility clients from millions of clients?
  - *Spatiotemporal* variation: heterogeneous utility across clients over rounds
- Exploration + Exploitation
  - Explore not-tried clients
  - Exploit known *high-utility* clients

Oort
Exploitation
Exploration
Client Pool

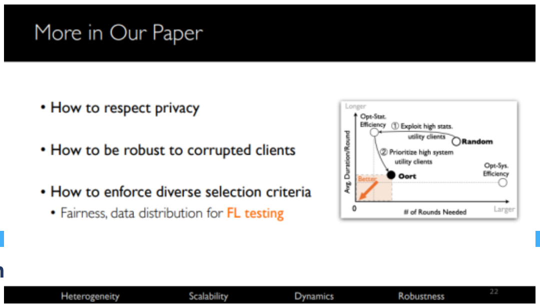


Challenge 3: Select High-Utility Clients Adaptively

- How to account for stale utility since last participation?
  - Utility changes due to dynamics

1. Aging: add uncertainty to utility $\longrightarrow$ *Re-discover missed good clients*
   - current_utility = last_observed_utility + *observation_age*
2. Probabilistic selection by utility values
   - Prioritize high-utility clients
   - Robust to outliers and uncertainties

Heterogeneity Scalability Dynamics Robustness 21



More in Our Paper

- How to respect privacy
- How to be robust to corrupted clients
- How to enforce diverse selection criteria
  - Fairness, data distribution for FL testing

Longer
Opt-Stat. Efficiency
① Exploit high stats. utility clients
Random
② Prioritize high system utility clients
Oort
Opt-Sys. Efficiency
Better
Avg. Duration/Round
0
# of Rounds Needed
Larger

Heterogeneity Scalability Dynamics Robustness 22

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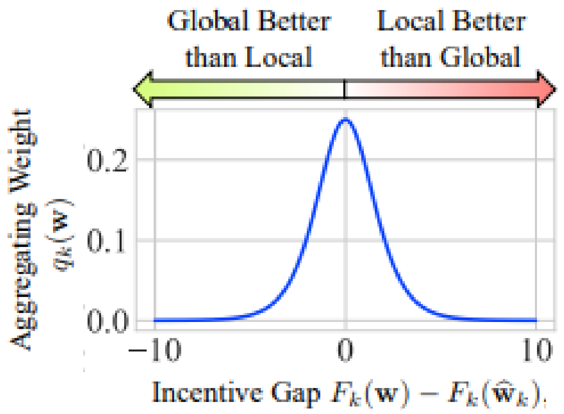
Client Selection

Yae Jee Cho, https://github.com/Kwangkee/FL/blob/main/FL@CarnegieMellon.md#yae-jee-cho

Towards Understanding Biased Client Selection in Federated Learning,
https://proceedings.mlr.press/v151/jee-cho22a.html
In our work, we present the convergence analysis of federated learning with biased client selection and quantify how the bias affects convergence speed. **We show that biasing client selection towards clients with higher local loss yields faster error convergence.**

To Federate or Not To Federate: Incentivizing Client Participation in Federated Learning,
https://arxiv.org/abs/2205.14840
Figure 2: Aggregating weight qk(w) for any clientk versus the emprical incentive gap Fk(w) − Fk(wb k). The weight qk(w) is small for clients that already have a very large incentive (global much better than local) or no incentive at all (local much better than global), and is highest for clients that are moderately incentivized (global similar to local).



Flower

Flower, https://flower.dev/
A Friendly Federated Learning Framework, A unified approach to federated learning. Federate any workload, any ML framework, and any programming language.
Github: https://github.com/adap/flower
Slack: https://friendly-flower.slack.com/ssb/redirect
Summit: https://flower.dev/conf/flower-summit-2021

Flower: A Friendly Federated Learning Research Framework, https://arxiv.org/abs/2007.14390
Youtube: https://www.youtube.com/watch?v=t5WdERBPQfk&t=1s
On-device Federated Learning with Flower, https://arxiv.org/abs/2104.03042
Youtube: https://www.youtube.com/watch?v=QJEX5c0y1I8&t=2s

Flower use case

Scaling Flower with Multiprocessing, https://towardsdatascience.com/scaling-flower-with-multiprocessing-a0bc7b7aace0
Github: https://github.com/matturche/flower_scaling_example

Learn how to scale locally your Federated Learning experiments using the Flower framework and multiprocessing with PyTorch.

How to solve the issue:
This problem that you might have encountered, can be solved quite easily. Since the memory is not released until the process accessing it is released, then we simply need to encapsulate the part of our code that need to access the GPU in a sub-process, waiting for it to be terminated until we can continue to execute our program. Multiprocessing is the solution, and I will show you how to do it using PyTorch and Flower.

Differentially Private Federated Learning with Flower and Opacus, https://towardsdatascience.com/differentially-private-federated-learning-with-flower-and-opacus-e14fb0d2d229
Github: https://github.com/matturche/flower_opacus_example

OpenFL

[intel]
OpenFL: An open-source framework for Federated Learning, https://arxiv.org/abs/2105.06413
Github: https://github.com/intel/openfl
YouTube: Federated Learning in Healthcare Use Cases | Intel Software,
https://www.youtube.com/watch?v=z5jJsvvfKbM
YouTube: SOSCON Russia 2021 [English]. Open리: Python library for Federated Learning. Olga Perepelkina, Intel, https://www.youtube.com/watch?v=Zso2oYsEgw0

인텔-펜실베니아大, 연합학습으로 환자 보안 유지하며 뇌종양 식별하는 AI 개발,
http://www.airtimes.kr/news/articleView.html?idxno=16331
https://www.apheris.com/blog-top7-open-source-frameworks-for-federated-learning

IBM Federated Learning, https://ibmfl.mybluemix.net/
Github: https://github.com/IBM/federated-learning-lib

OpenMined, https://www.openmined.org/
Github: https://github.com/OpenMined/PySyft

FedML: A Research Library and Benchmark for Federated Machine Learning, https://fedml.ai/
Github: https://github.com/FedML-AI

OpenFL

[intel] OpenFL: An open-source framework for Federated Learning, https://arxiv.org/abs/2105.06413

Abstract. Federated learning (FL) is a computational paradigm that enables organizations to collaborate on machine learning (ML) projects without sharing sensitive data, such as, patient records, financial data, or classified secrets.
Open Federated Learning (OpenFL) is an open-source framework for training ML algorithms using the data-private collaborative learning paradigm of FL. OpenFL works with training pipelines built with both TensorFlow and PyTorch, and can be easily extended to other ML and deep learning frameworks.
Here, we summarize the motivation and development characteristics of OpenFL, with the intention of facilitating its application to existing ML model training in a production environment.

Finally, we describe the first use of the OpenFL framework to train consensus ML models in a consortium of international healthcare organizations, as well as how it facilitates the first computational competition on FL.

Our ambition is that federations, such as the FeTS Initiative, will not serve as ad hoc collaborations for specific research efforts, but will serve as permanent networks for researchers in the healthcare, financial, industrial, and retail industries to more effectively train, deploy, monitor, and update their AI algorithms over time.

FeTS : https://www.fets.ai

OpenFL

[intel] OpenFL: An open-source framework for Federated Learning, https://arxiv.org/abs/2105.06413

3.2 First Computational Competition on Federated Learning

As the first challenge ever proposed for federated learning, the FeTS challenge 20212 intends to address these hurdles towards both the creation and the evaluation of tumor segmentation models. Specifically, the FeTS 2021 challenge uses clinically acquired, multi-institutional MRI scans from the BraTS 2020 challenge [18–20], as well as from various remote independent institutions included in the collaborative network of a real-world federation.

Federated Tumor Segmentation Challenge 2021, https://fets-ai.github.io/Challenge/

Compared to the BraTS challenge, the ultimate goal of the FeTS challenge is divided into the following two tasks:

1. Task 1 (“Federated Training”) aims at effective weight aggregation methods for the creation of a consensus model given a pre-defined segmentation algorithm for training, while also (optionally) accounting for network outages.
2. Task 2 (“Federated Evaluation”) aims at robust segmentation algorithms, given a pre-defined weight aggregation method, evaluated during the testing phase on unseen datasets from various remote independent institutions of the collaborative network of the fets.ai federation.

Nevermined

Nevermined, https://www.nevermined.io/

Nevermined is a data ecosystem solution that provides the capabilities of building bespoke networks where different entities can share and monetize their data and make an efficient and secure usage of it even with untrusted parties.

Github: https://github.com/nevermined-io
Docs: https://docs.nevermined.io/
Blog: https://docs.nevermined.io/Blog/

YouTube: Leveraging blockchain to unlock data for federated learning,
https://www.youtube.com/watch?v=A0A9hSlPhKI
Description: This demo we will be using Flower and Nevermined with the goal of the model to train classify images given two different datasets.

Data Monetization for Enterprises, https://multimedia.getresponse.com/getresponse-ylcbE/documents/12e30a17-5321-49cd-a613-963451401b07.pdf

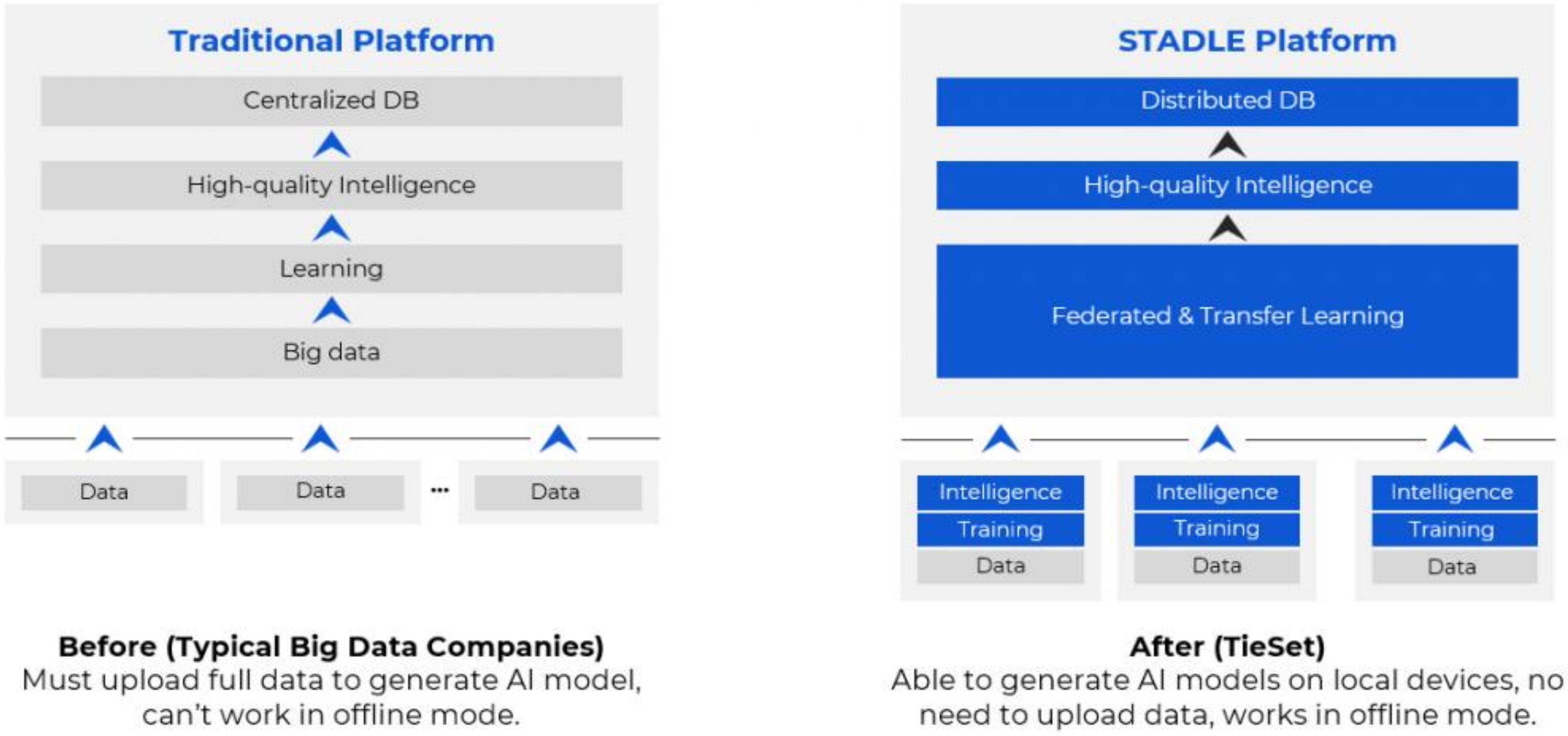
https://www.nevermined.io/solutions/details/data-sharing#federated-learning
https://www.nevermined.io/solutions/details/data-governance#incentives

- One of the most powerful features of blockchain technology is the ability to issue incentives, rewards, and penalties for specific activity. In Bitcoin, the incentive manifests as block rewards for miners operating computers with the largest computational power. This ability to bake in incentives that promote participant behavior provides a fundamental shift in how digital ecosystems operate, including how they are monetized as well as governed.

STADLE

STADLE: https://www.stadle.ai/
TieSet Website: https://tie-set.com/
Doc/Install: https://stadle-documentation.readthedocs.io/en/latest/overview.html

Introduction to TieSet, https://www.youtube.com/watch?v=Nk9gdsFBKGs
YouTube: https://www.youtube.com/channel/UCv3NW3foNBRv12q-ymKa37A



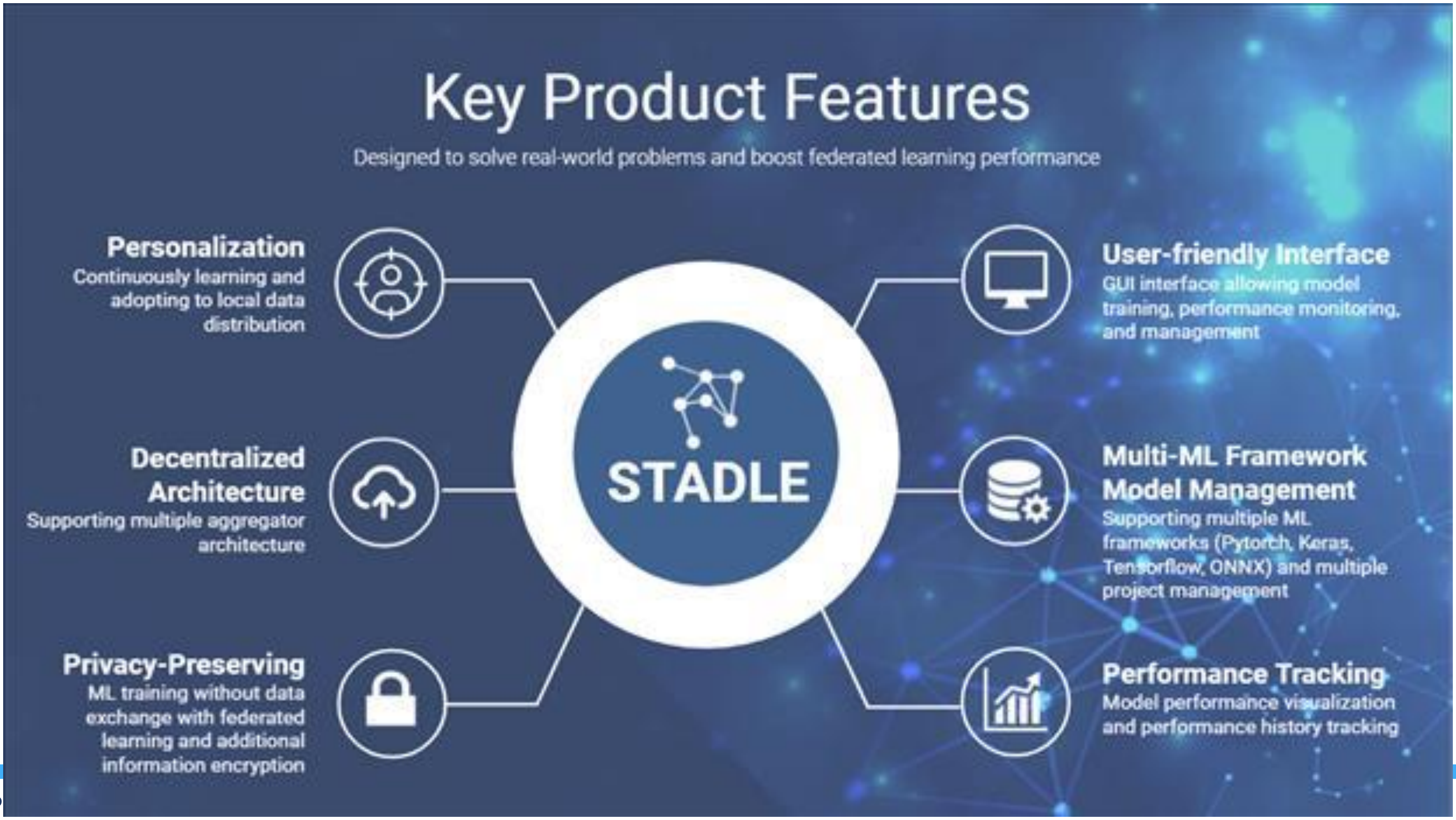
Before (Typical Big Data Companies)
Must upload full data to generate AI model, can't work in offline mode.

After (TieSet)
Able to generate AI models on local devices, no need to upload data, works in offline mode.

STADLE

STADLE: https://www.stadle.ai/
TieSet Website: https://tie-set.com/
Doc/Install: https://stadle-documentation.readthedocs.io/en/latest/overview.html

Introduction to TieSet, https://www.youtube.com/watch?v=Nk9gdsFBKGs
YouTube: https://www.youtube.com/channel/UCv3NW3foNBRv12q-ymKa37A
TieSet Team 1 min intro, https://www.youtube.com/watch?v=vURWKP1jrv0


Key Product Features
Designed to solve real-world problems and boost federated learning performance
STADLE
Personalization
Continuously learning and adopting to local data distribution
Decentralized Architecture
Supporting multiple aggregator architecture
Privacy-Preserving
ML training without data exchange with federated learning and additional information encryption
User-friendly Interface
GUI interface allowing model training, performance monitoring, and management
Multi-ML Framework Model Management
Supporting multiple ML frameworks (Pytorch, Keras, Tensorflow, ONNX) and multiple project management
Performance Tracking
Model performance visualization and performance history tracking

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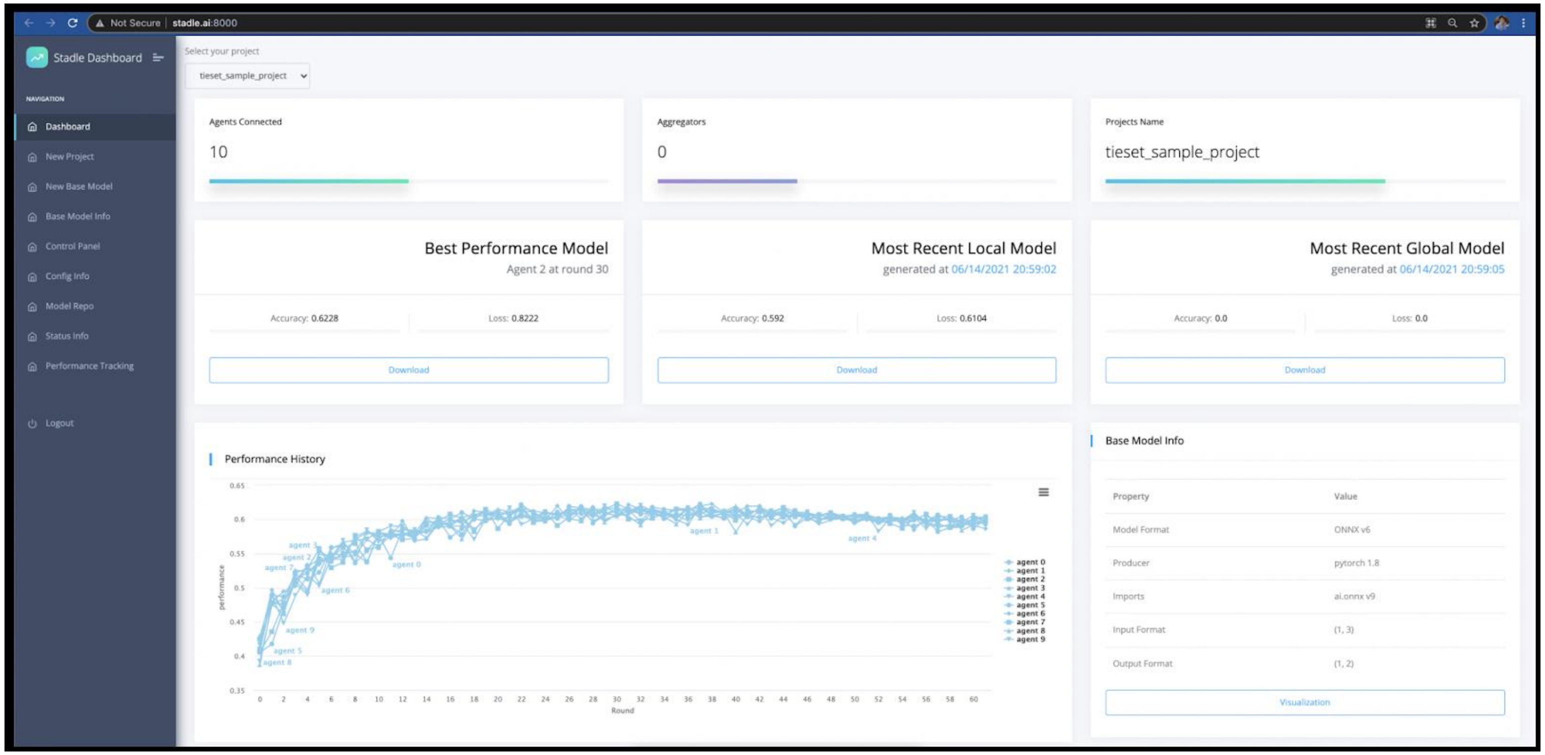
News: https://re-how.net/all/1380746/
Now that we have completed the development of the basic functions for commercialization, we have decided to carry out a private release. With this release, further functional improvements and commercialization of this platform To promote this, we are looking for a partner who can carry out both technical verification and verification verification.



Agents Connected
10

Aggregators
0

Projects Name
tieset_sample_project

Best Performance Model
Agent 2 at round 30
Accuracy: 0.6228 Loss: 0.8222

Most Recent Local Model
generated at 06/14/2021 20:59:02
Accuracy: 0.592 Loss: 0.6104

Most Recent Global Model
generated at 06/14/2021 20:59:05
Accuracy: 0.0 Loss: 0.0

Base Model Info

Property	Value
Model Format	ONNX v6
Producer	pytorch 1.8
Imports	ai.onnx v9
Input Format	(1, 3)
Output Format	(1, 2)

PowerFlow

PowerFlow: https://integrate.ai/powerflow/
Design a federated learning system in seven steps, https://integrate.ai/blog/design-a-federated-learning-system-in-seven-steps-pftl/

Etc.

Federated Learning in Heterogeneous Environments, https://www.youtube.com/watch?v=651VFm2vIhA