Department of Computer Science and Engineering CS6811 Final Year Project [2023]

A PRIVACY PRESERVING FEDERATED LEARNING PLATFORM SECURED WITH AUTHORITY CONSENSUS USING BLOCKCHAIN

Project Guide

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BASE PAPER

BAFL: A Blockchain-Based Asynchronous Federated Learning Framework

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BAFL: A Blockchain-Based Asynchronous Federated Learning Framework

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Abstract—As an emerging distributed machine learning (ML) method, federated learning (FL) can protect data privacy through collaborative learning of artificial intelligence (Al) models across a large number of devices. However, inefficiency and vulnerability to posoning attacks have slowed FL performance. Therefore, a blockchain-based asynctronous federated learning (BAFL) framework is proposed to ensure the security and efficiency required by FL. The blockchain ensures that the model data cannot be tampered with white asynchronous learning speeds up (global aggregation. A novel entropy weight method is used to evaluate the participating with and proportion of the local model trained in BAFL of the devices. The energy consumption and local model update efficiency are balanced by adjusting the local training and communication delay and optimizing the block (spenaration stat. The extensive evaluation results show that the proposed BAFL framework has higher efficiency and higher performance for preventing poisoning attacks than other distributed bill methods.

Index Terms—Blockchain, federated learning, security, asynchronous learning, learning efficiency

1 INTRODUCTION

Due to the rapid development of machine learning methods, many novel mobile applications using this method have emerged, such as automated driving, sales forecasting, and visual security, improving the users' service experience [1]. Although machine learning has significantly improved the performance of mobile applications, traditional machine learning methods used in the networks require numerous devices to store data with personal information in a central server to perform model training. This has led to a sharp rise in computing overhead and losses on the central server. Meanwhile, the need to centralize user data has raised concerns about privacy and information abuse [2]. Federated learning (FL), a distributed machine learning method, has been developed to address these challenges. Federated learning trains a global model in a decentralized manner. The mobile device iteratively trains the local model, uploads the local training model, and sends it to the central server. Because there is no transfer of raw user data [3], to some content, FL protects the user's privacy and decouples the machine learning processes of data acquisition, training, and storing models on a central server.

However, there are several limitations for traditional FL applying in networks. The first limitation is the reliability of the learning model for each device. Malicious devices can adversely affect the global model by tweaking the local

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model. Second, the FL process is entirely dependent on the reliability of the central server. If the central server fails or maliciously modifies the global model, the updating accuracy of all subsequent local models will be substantially reduced. Another problem is the lag effect, which means that each round of training can only be performed at the training speed of the slowest device. This makes it impossible for a highly computational device to upload the local model in time after the local update has been completed.

In this paper, a blockchain-enabled asynchronous federated learning (BAFL) architecture is proposed that combines the blockchain with asynchronous FL, with the advantages of trust and learning efficiency. The main contributions of this paper are as follows:

- Unlike traditional FL, the proposed BAFL uses an asynchronous FL strategy that allows each device to upload the local model whenever the global aggregation requires fast convergence of the global model. The blockchain also prevents the failure of a single central server and guarantees decentralized and secure data storage. In addition, the blockchain motivates devices by rewarding them for participating in FL.
- Two complementary policies are designed for BAFL workflow to guarantee the efficiency of blockchain enabled FL. The first is to optimally control the block generation rate to reduce the delay of FL. The second is the dynamic adjustment of the number of training times in asynchronous FL to prevent frequent uploading of the local model from causing blockchain transaction overloads.
- Instead of the traditional federal average (FedAvg) algorithm, this paper evaluates the participating rank and proportion of the local model trained in BAFL of devices. The indices, which consider the

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INTRODUCTION

- In recent years, there has been an enormous corpus of research and development dedicated to and focused on accelerating the processes of machine learning in every conceivable shape or form.
- This provides greater flexibility and interoperability features than Monolith as they are easily scalable and robust to failures.
- Computer hardware was not adequate enough to handle already existing machine learning algorithms, yet it seems the rapidly growing demand for machine learning applications has put us in a situation that yet again undermines the capabilities of individual machines.
- The Solution for this problem is to multiple machines collaborate on training the model at hand.

INTRODUCTION

- The idea of federated learning solves another major problem: the scarcity of data at a single machine. This is solved through the collaboration of different nodes in the training, each using its local data then sharing its model updates, realizing a single model trained on the sum of their local data.
- In Federated Learning, they train it on their private data, then summarize and encrypt the model's new configuration. The model updates are sent back to the cloud, decrypted, averaged, and integrated into the centralized model. Iteration after iteration, the collaborative training continues until the model is fully trained.
- DFedL offers feasible solutions to common challenges in decentralized federated learning, namely, privacy, efficiency, and Byzantine fault-tolerance.

OVERALL OBJECTIVES

- To achieve federated learning over decentralized network which eliminates following issues:
 - Central node inferring important information
 - Single point of failure on the server node
- To prevent malicious clients, who tries to attack the global model with incorrect gradients (Byzantine Imposter)
- To solve the issue of expensive communication where each training node shares its update with all the other nodes using authority consensus

LITERATURE SURVEY

SNO	TITLE	METHODOLOGY	ADVANTAGES	LIMITATIONS
1	Federated Learning System without Model Sharing through Integration of Dimensional Reduced Data Representations (2020)	Explored an federated learning system that enables integration of dimensionality reduced representations of distributed data prior to a supervised learning task, thus avoiding model sharing among the parties.	The Results show that this approach can achieve similar accuracy as Federated Averaging and performs better than Federated Averaging in a small-user setting.	Dimensionlity reduction may reduce accuracy in some cases

LITERATURE SURVEY

SNO	TITLE	METHODOLOGY	ADVANTAGES	LIMITATIONS
2	Trustless Machine Learning Contracts; Evaluating and Exchanging Machine Learning Models on the Ethereum Blockchain (2018)	This paper discovered that it is possible to create contracts that offer a reward in exchange for a trained machine learning model for a particular data set. This would allow users to train machine learning models for a reward in a trustless manner. Contracts can be created easily by anyone with a dataset, even programmatically by software agents.	creation of better machine learning	Without better design it leads to increase in gas cost

SNO	TITLE	METHODOLOGY	ADVANTAGES	LIMITATIONS
3	Comparative Study of Byzantine Fault Tolerant Consensus Algorithms on Permissioned Blockchains (2020)	This paper provides idea for the private blockchains to use permissioned blockchain consensus algorithms as the participants need the permission of the authority to be able to join the system and investigated permissioned and permissionless blockchain,	Trust models between the nodes, incentives, number of nodes & parties involved, and scalability regarding the number of transactions.	Each business application has different problems and priorities which is hard to generalise.
4	Federated Learning: Strategies for Improving Communication Efficiency (2017)	This paper proposed two ways to reduce the uplink communication costs in implementing federated learning: structured updates and sketched updates	Both convolutional and recurrent networks show that the proposed methods can reduce the communication cost by two orders of magnitude.	Reducing communication cost may lead to downside of security.

SNO	TITLE	METHODOLOGY	ADVANTAGES	LIMITATIONS
5	Consensus- Based Data- Privacy Preserving Data Aggregation (2019)	This paper addresses to solve the challenges in privacy preserving data aggregation by exploiting the distributed consensus technique. They first proposed a secure consensus-based DA algorithm that guarantees an accurate sum aggregation while preserving the privacy of sensitive data, then proved that the proposed algorithm converges accurately.	have shown that the proposed algorithm has high accuracy and low complexity, and they are robust against	Intensive simulation may lead to low accuracy and high complexity
6	A PoW-less Bitcoin with Certified Byzantine Consensus (2022)	This paper explored one possible way to solve the problem where the Distributed Ledger Technologies, when managed by a few trusted checkers requires most but not all of the machinery available in public DLTs.	protocol may operate as a modern,safe	PoA is more centralised compared to PoW

SNO	TITLE	METHODOLOGY	ADVANTAGES	LIMITATIONS
7	Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data (2020)	This paper investigated the effects of data distribution across collaborating institutions on model quality and learning patterns, indicating that increased access to data through data private multi-institutional collaborations can benefit model quality more than the errors introduced by the collaborative method.	Models having a catalytic impact towards precision/persona lized medicine.	Errors may occur if done in small scale
8	Privacy-Preserving Resource Sharing Using Permissioned Blockchains, (2021)	Designed a decentralized resource sharing platform that uses a permissioned blockchain to allow users to share their digital items with their specified attributed-based access policies that are enforced through a set of smart contracts, and removes the need for a trusted intermediary.	This decentralized attribute-based access control system achieves the same functionality while preserving the privacy of user's access	It has limited availability, has access to the resource requires it's owner to be online.

SNO	TITLE	METHODOLOGY	ADVANTAGES	LIMITATIONS
9	A Hybrid Approach to Privacy- Preserving Federated Learning (2019)	This paper proposed a Hybrid Approach to Privacy-Preserving Federated Learning by Combining differential privacy with secure multiparty computation which enables to reduce the growth of noise injection as the number of parties increases without sacrificing privacy while maintaining a predefined rate of trust.	This system can be used to train a variety of machine learning models, which demonstrate that our approach out-performs state of the art solutions.	Hybrid approach leads to moderate privacy and security
10	Blockchain-enabled Federated Learning: A Survey (2023)	Introduced a Blockchain-enabled Federated Learning that has been and will keep generating widespread attention in this big data era. However, the existing paradigms become increasingly impractical and difficult to follow from both perspectives of introductory and in-depth exploration of state-of-theart models.	Systematically introduced the evaluation matrix and analysis criteria	Lacking consensus algorithm as it may be prone to attacks

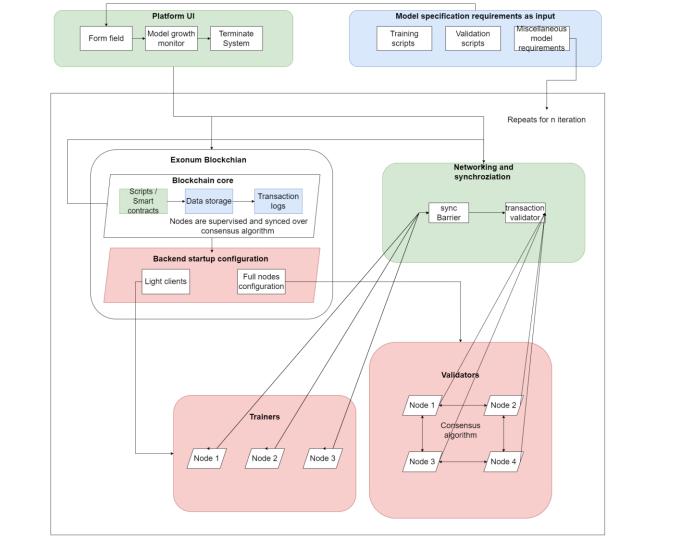
SUMMARY OF ISSUES

- Each business application has different problems and priorities which is hard to generalize.
- Reducing communication costs may lead to downside of security.
- Intensive simulation may lead to low accuracy and high complexity.
- Proof of Authority is more centralized when compared with Proof of Work.

PROPOSED SYSTEM

- We propose a framework Decentralized Federated Learning (DFedL) for building a generic decentralized federated learning system using the blockchain technology, accommodating any machine learning model that is compatible with gradient descent optimization.
- DFedL uses proof-of-concept used to spawn mini-systems checkers and clients.
 The system design comprising of two decentralized actors: client and checker,
 alongside the methodology for ensuring reliable and efficient operation of the
 system.
- Hence, DFedL as an experimental sandbox to compare and contrast the effects of client-to-checker ratio, reward-penalty policy, and model synchronization schemes on the overall system performance, ultimately showing by example that a decentralized federated learning system is indeed a feasible alternative to more centralized architectures.

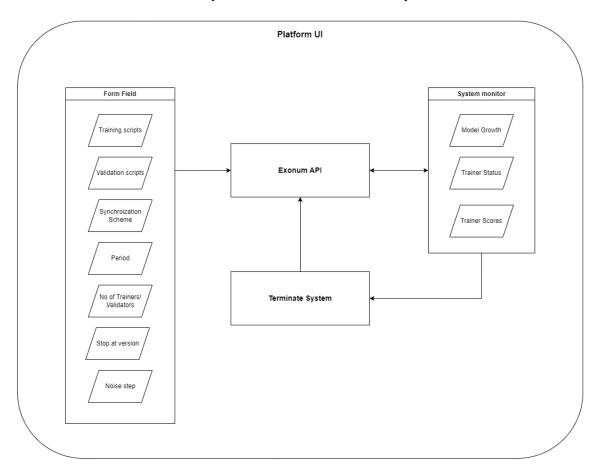
ARCHITECTURE DIAGRAM



LIST OF MODULES

- 1) Model Specification and platform UI
- 2) Blockchain core and startup configuration
- 3) Networking and synchronization
- 4) Model clients
- 5) Model checkers

Module 1 - Model Specification and platform UI



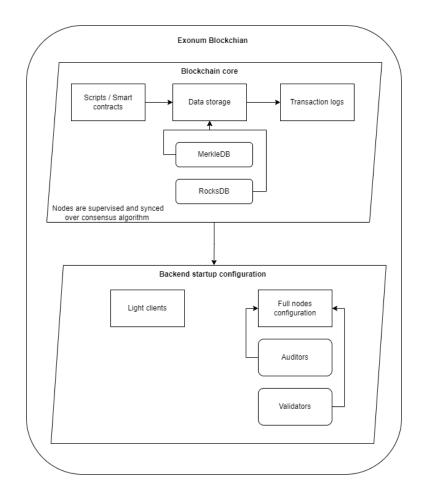
Module 1 - Model Specification and platform UI

INPUT: Training and validation Scripts and Number, Synchronization scheme, Noise step OUTPUT: Forwards to startup configuration.

STEPS:

- 1)Develop application to get the scripts to distribute them across clients and checkers to train the local dataset upon it.
- 2) User can configure the system to run model
- 3) Configuration can be done on
 - O fixing amount of clients and checkers,
 - O choice on Synchronization Scheme (BAP, BSP, SSP),
 - Stop at version
 - Noise step
- 3) To monitor the model growth system is equipped with client status and client scores
- 4) Creating the jobs and start training
- 5) Terminating thre process

Module 2 - Blockchain core and startup configuration



Module 2 - Blockchain core and startup configuration (1/2)

INPUT: Parameters for Environment Creation OUTPUT: checkers and clients Environment

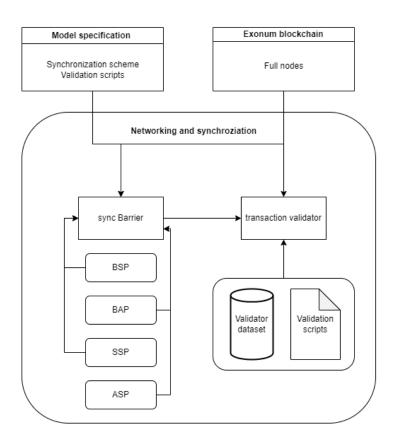
- Data storage, which contains data structured into objects. Objects represent high-level wrappers over the key-value store.
- 2) Transaction log, i.e., the complete history of all transactions ever applied to the data storage.
- 3) Exonum gathers transactions into blocks; the whole block is approved atomically.
- 4) After a block is approved, every transaction in it is executed sequentially, with changes applied to the data storage.
- 5) Smart contracts define business logic of the blockchain, allow to retrieve data from the blockchain, and can be reused across different projects.

Module 2 - Blockchain core and startup configuration (2/2)

STEPS:

- 1) Full nodes replicate the entire contents of the blockchain and correspond to replicas in distributed databases. All the full nodes are authenticated with public-key cryptography.
- 2) Full nodes are further subdivided into 2 categories Auditors and checkers
- 3) Auditors replicate the entire content of the blockchain. They can generate new transactions, but cannot choose which transactions should be committed
- 4) Only checkers can generate new blocks by using a Byzantine fault tolerant consensus algorithm. checkers receive transactions, verify them, and include into a new block.
- 5) Light clients represent clients in the client-server paradigm; they connect to full nodes to retrieve information from the blockchain they are interested in and to send transactions.

Module 3 - Networking and synchronization



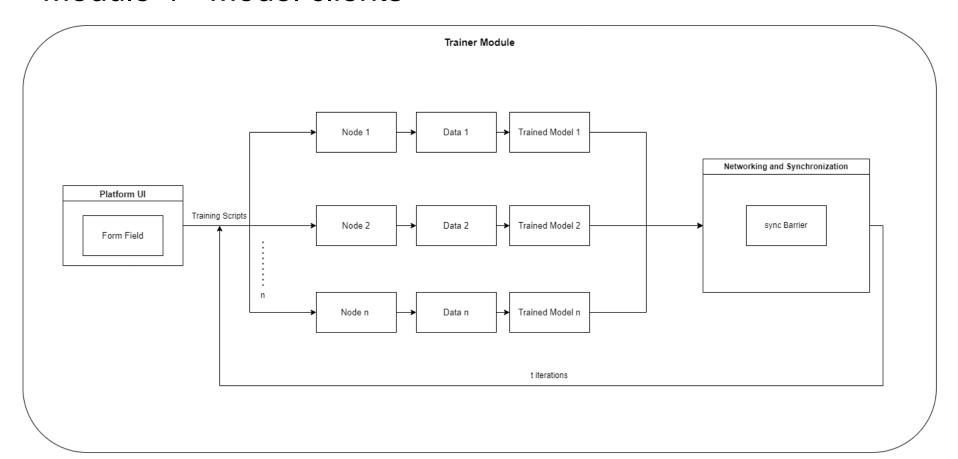
Module 3 - Elastic Scalability (2/2)

INPUT: Sync updated parameters from clients and validates with checkers

OUTPUT: Commits the transaction logs in exonum blockchain

- 1. There are many techniques to handle node update synchronization to prevent model degradation
- 2. In Bulk Synchronous Parallel (BSP) each training round is limited by a fixed period that ends with a strict deadline after which no further client updates are considered for that round.
- 3. In Stale Synchronous Parallel (SSP) SSP is modelled as BSP with the possibility of a deadline extension when proportion to the ratio of clients that have not yet finished training for that round
- 4. Barrierless Asynchronous Parallel (BAP) BSP as it almost totally eliminates the cost of synchronization by allowing wait less, asynchronous communication between nodes
- 5. Trust scores are adjusted based on validation results.
- 6. Upon receiving a client update, a checker adds its gradients to the latest model weights, and computes its validation score.

Module 4 - Model clients



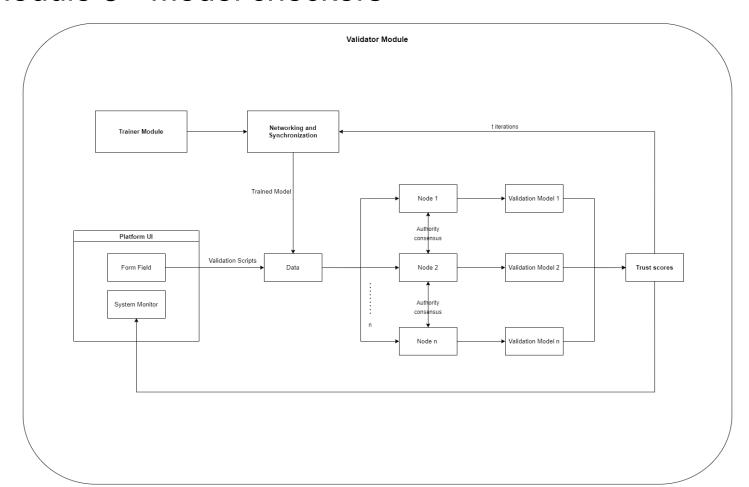
Module 4 - Model clients

INPUT: client scripts

OUTPUT: Updated model parameters

- Performs model training including all needed intermediate transformations such as model flattening and rebuilding at the client side.
- This layer sends and receives flattened models and flattened gradients built on top of exonum lightweight clients.
- To improve system auditability, Exonum includes a light client. Light client is a JavaScript library with a number of helper functions available for use by frontend developers.
- There are two typical use cases for the light client forming and sending transactions to the Exonum blockchain network
- Forming requests to full nodes of the network (normally, HTTP GET requests) and validation of the responses

Module 5 - Model checkers



Module 5 - Model checkers

INPUT: Updated model parameters and client scripts.

OUTPUT: Trust scores

- checkers are responsible for maintaining models on the underlying blockchain network through decentralized consensus based on voting.
- Ideally, a checker's vote, on whether some update to the model (made by a client node) is acceptable, should be
 decided by validation on data presumably unrevealed to the client.
- That, combined with the voting-based nature of consensus, stipulates the following requirements and assumptions in order for the system to operate soundly.
- One important property is that clients are not fully connected to the checkers while checkers are fully interconnected.
- yet a node can be a checker on a subnetwork while being a client for another. Further, each model subnetwork requires at least one checker to function.

IMPLEMENTATION DETAILS

Blockchain Setup (Exonum):

Exonum is written in Rust and depends on the following third-party system libraries:

- RocksDB (persistent storage)
- libsodium (cryptography engine)
- Protocol Buffers (mechanism for serializing structured data)

Prerequisites:

- git
- Node.js with npm
- Rust compiler
- Exonum launcher

Dependencies installation:

For distributives with deb-based package managers (such as Debian or Ubuntu), use

```
add-apt-repository ppa:exonum/rocksdb
apt-get update
apt-get install build-essential jq libsodium-dev
libsnappy-dev libssl-dev \
    librocksdb6.2 pkg-config clang-7 lldb-7 lld-7
```

For protobuf installation add the following dependencies:

```
add-apt-repository ppa:maarten-fonville/protobuf apt install libprotobuf-dev protobuf-compiler
```

Package names and installation methods may differ in other Linux distributives; use package manager tools to locate and install dependencies.

Depending on the version of your distributive, libsodium, RocksDB and Protobuf may not be present in the default package lists. In this case you may need to install these packages from third-party PPAs, or build them from sources.

Adding Environment Variables

If your OS contains pre-compiled rocksdb or snappy libraries, you may setup ROCKSDB_LIB_DIR and/or SNAPPY_LIB_DIR environment variable to point to a directory with these libraries. This will significantly reduce compile time.

```
export ROCKSDB_LIB_DIR=/usr/lib
export SNAPPY_LIB_DIR=/usr/lib/x86_64-linux-gnu
```

Rust Toolchain

Exonum repositories use the stable Rust toolchain that can be installed by using the <u>rustup</u> program:

```
curl https://sh.rustup.rs -sSf | sh -s -- --default-
toolchain stable
```

Compiling Exonum

We can verify that you installed dependencies and the Rust toolchain correctly by cloning the exonum repository and running its built-in unit test suite:

```
git clone https://github.com/exonum/exonum.git
cd exonum
cargo test -p exonum
```

Necessary dependencies(Cargo.toml):

```
[package]
name = "cryptocurrency"
version = "0.1.0"
edition = "2018"
authors = ["Your Name <your@email.com>"]

[dependencies]
exonum = "1.0.0"
exonum-crypto = "1.0.0"
exonum-derive = "1.0.0"
exonum-proto = "1.0.0"
exonum-rust-runtime = "1.0.0"
```

```
failure = "0.1.5"
protobuf = "2.8.0"
serde = "1.0"
serde_derive = "1.0"
serde_json = "1.0"

[build-dependencies]
exonum-build = "1.0.0"
```

NECESSARY DEPENDENCIES

NECESSARY DEPENDENCIES

Generate node configuration template:

```
mkdir example
exonum-<project-name> generate-template \
   example/common.toml \
   --checkers-count 4
```

Generate public and secret keys for each node:

```
exonum-<project-name> -advanced generate-config \
 example/common.toml example/1 \
  --peer-address 127.0.0.1:6331 -n
exonum-<project-name> generate-config \
 example/common.toml example/2 \
  --peer-address 127.0.0.1:6332 -n
exonum-oject-name> generate-config \
 example/common.toml example/3 \
  --peer-address 127.0.0.1:6333 -n
exonum-<project-name> generate-config \
 example/common.toml example/4 \
  --peer-address 127.0.0.1:6334 -n
```

Finalize configs:

```
exonum-<project-name> finalize \
   --public-api-address 0.0.0.0:8200 \
   --private-api-address 0.0.0.0:8091 \
   example/1/sec.toml example/1/node.toml \
   --public-configs example/{1,2,3,4}/pub.toml
```

Similar commands for other 3 nodes, with adjusted paths and socket addresses

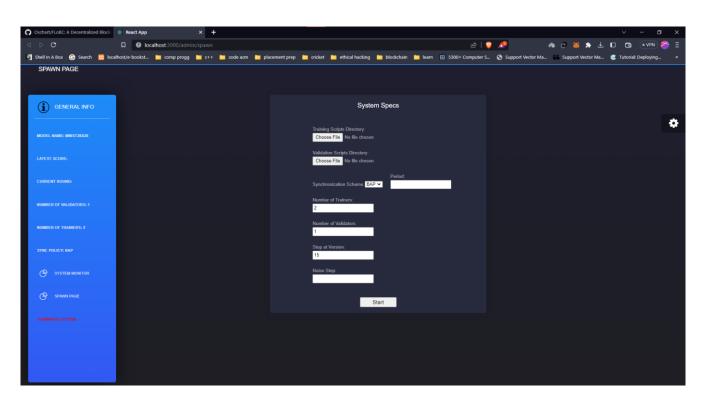
Run nodes:

```
exonum--ct-name> run \
   --node-config example/1/node.toml \
   --db-path example/1/db \
   --public-api-address 0.0.0.0:8200 \
   --master-key-pass pass
```

Similar commands for other 3 nodes, with adjusted paths and socket addresses

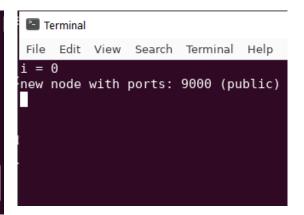
Filling Requirements in Spawn Page:

Frontend is connected to node server via REST api. All the requirements to spawn the system is passed to node server which will run script to initiate client and checker nodes



Starting checker Node:

Backend node spawn script starts the mentioned number of checkers and the checker nodes starts receiving for model updates by the clients



checker WAITING FOR MODEL UPDATE BY clients

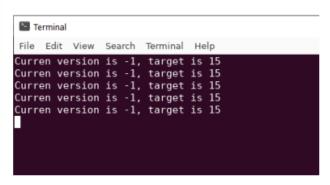
Backend node spawn script starts the mentioned number of clients that trains the model with local data and sends it to the checker node

```
1
'./lightclient' -> './/lightclient1'
'./lightclient/.babelrc' -> './/lightclient1/.babelrc'
'./lightclient/models' -> './/lightclient1/models'
'./lightclient/models/MNIST20X20' -> './/lightclient1/models/MNIST20X20'
'./lightclient/models/MNIST20X20/apply.py' -> './/lightclient1/models/MNIST20X20/ap
ply.py'
'./lightclient/models/MNIST20X20/metadata' -> './/lightclient1/models/MNIST20X20/me
tadata'
'./lightclient/models/MNIST20X20/training_script.pv' -> './/lightclient1/models/MNI
ST20X20/training_script.py'
lightclient/models/MNIST20X20/utils.py' -> './/lightclient1/models/MNIST20X20/utils
'./lightclient/models/MNIST28X28' -> './/lightclient1/models/MNIST28X28'
'./lightclient/models/MNIST28X28/metadata' -> './/lightclient1/models/MNIST28X28/me
tadata'
'./lightclient/models/MNIST28X28/training_script.py' -> './/lightclient1/models/MNI
ST28X28/training_script.py'
'./lightclient/models/MNIST28X28/utils.py' -> './/lightclient1/models/MNIST28X28/ut
ils.pv'
'./lightclient/models/MNIST28X28/__pycache__' -> './/light
```

Starting checker Node:

Version manager is used to manage the current version of the released model with the target version

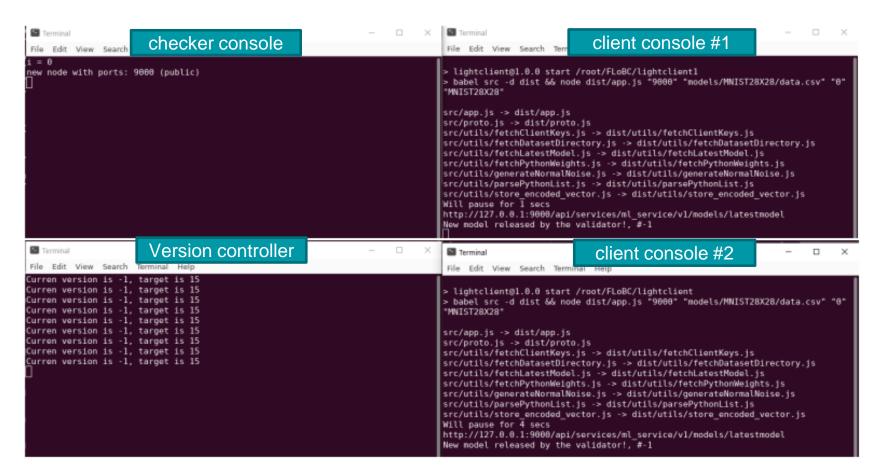
```
Terminal
 File Edit View Search Terminal Help
> lightclient@1.0.0 start /root/FLoBC/lightclient1
> babel src -d dist && node dist/app.is "9000" "models/MNIST28X28/data.csv" "0"
"MNIST28X28"
src/app.js -> dist/app.js
src/proto.js -> dist/proto.js
src/utils/fetchClientKeys.js -> dist/utils/fetchClientKeys.js
src/utils/fetchDatasetDirectory.js -> dist/utils/fetchDatasetDirectory.js
src/utils/fetchLatestModel.js -> dist/utils/fetchLatestModel.js
src/utils/fetchPythonWeights.js -> dist/utils/fetchPythonWeights.js
src/utils/generateNormalNoise.js -> dist/utils/generateNormalNoise.js
src/utils/parsePythonList.js -> dist/utils/parsePythonList.js
src/utils/store encoded vector.js -> dist/utils/store encoded vector.js
Will pause for \overline{1} secs
http://127.0.0.1:9000/api/services/ml service/v1/models/latestmodel
New model released by the validator!, #-1
```



LIGHT CLIENT #1

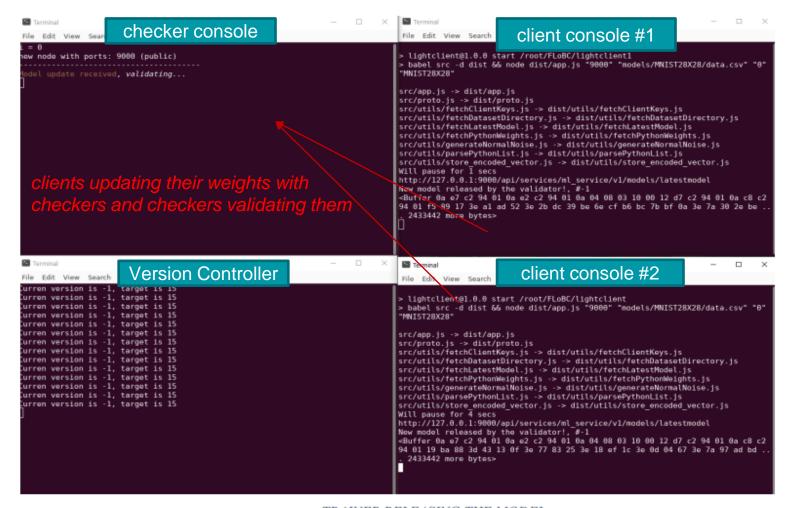
VERSION MANAGER

Due to CPU restrictions, we have done the demo for 2 clients and 1 checker. Further this can be extended with the help of powerful CPUs



Model Released by client:

client trains the model with local data and shares the model parameters with the checkers, asynchronously. clients are allowed to train for as long as a round may extend; that is, until a new model is released, clients can keep advancing local training, periodically sharing it with a checker. A new model is released when a minimum ratio of labor has been submitted, and that's when clients should pull in the new model.



Validating Model:

The model released by the client is validated by the checker using validating sample to check for any Byzantine attack. If the model accuracy is greater than the threshold accuracy then new model version is released by aggregating the previous version with the current version using aggregator function. Then the new aggregated model is synced across other checkers and clients. If the current version reaches the target version then the model is available for download.

```
Terminal

File Edit View Search Terminal Help

i = 0

new node with ports: 9000 (public)

Model update received, validating...

Output Output { status: ExitStatus(unix_wait_status(0)), stdout: "VALID:0.910799 9801635742\n", stderr: "" }

Validation verdict: VALID

New Model Created:: version= 1 accuracy= 91.08%

Model update received, validating...
```

VALIDATOR VALIDATING THE MODEL

Releasing Model:

```
Terminal

File Edit View Search Terminal Help

i = 0
new node with ports: 9000 (public)

Model update received, validating...

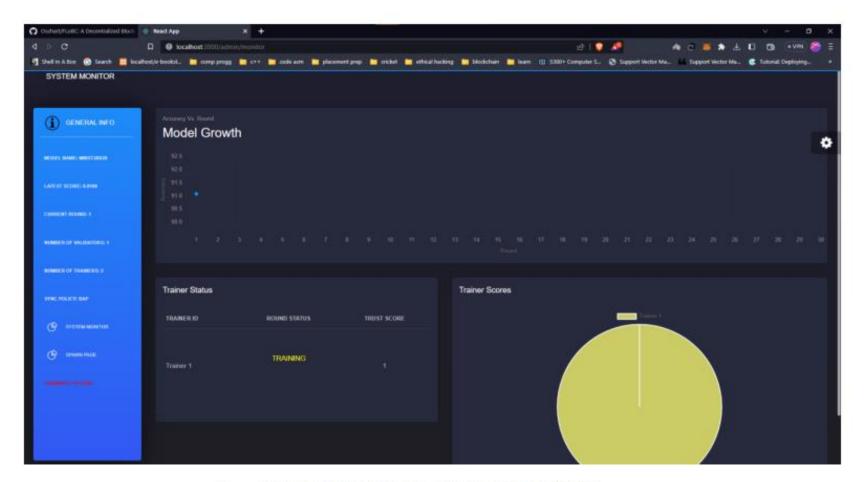
Output Output { status: ExitStatus(unix_wait_status(0)), stdout: "VALID:0.910799 9801635742\n", stderr: "" }

Validation verdict: VALID

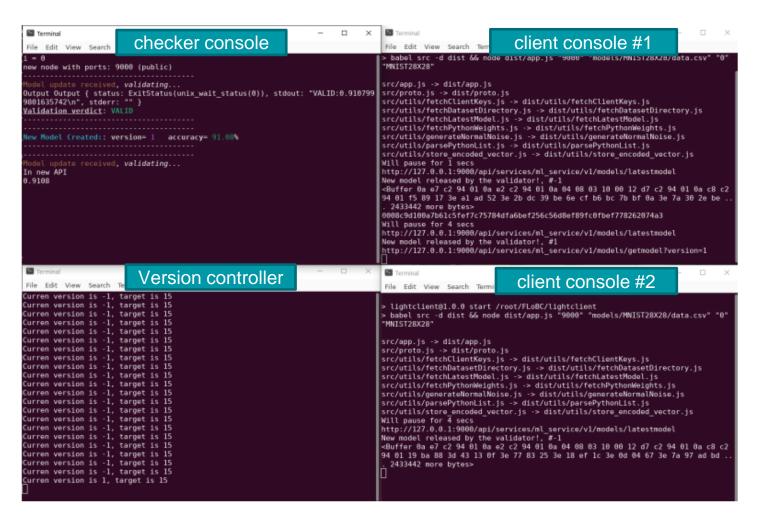
New Model Created: version= 1 accuracy= 91.08%

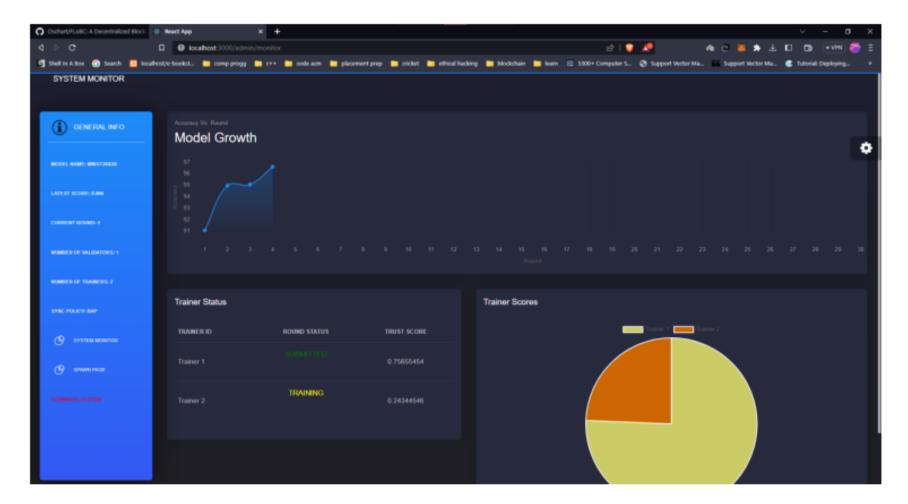
Model update received, validating...
```

Figure 23.1. VALIDATOR CREATING NEW MODEL

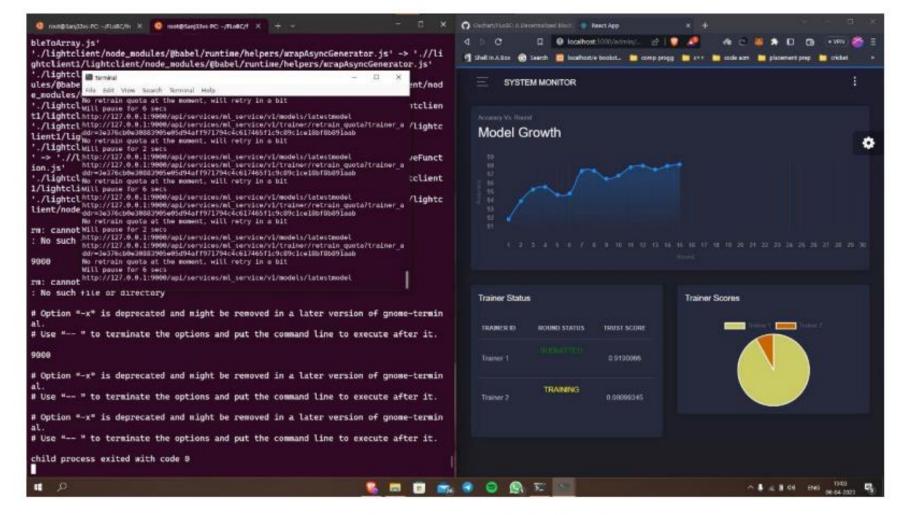


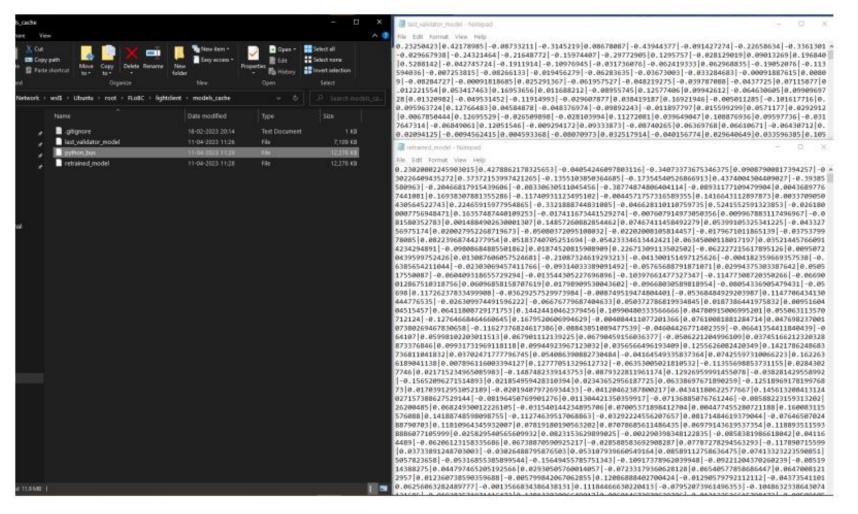
NEW MODEL REFLECTED IN DASHBOARD

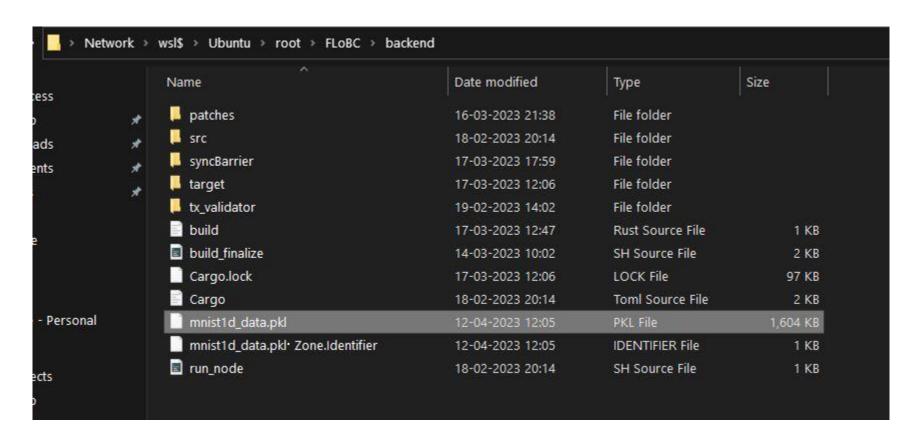




MODEL VERSION #4







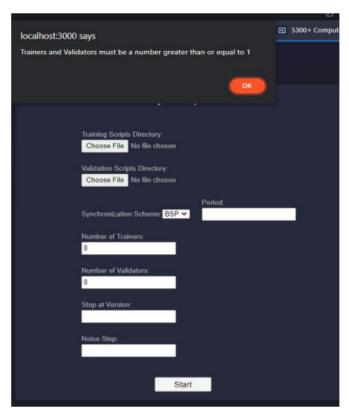
Finally, the trained model has been downloaded

TEST CASES

When clients and checkers are less than or equal to 0	<u>Link</u>
When period is 0 and the scheme is synchronous	<u>Link</u>
When spot at version is left null or is filled with float value	Link
Force Terminating System	<u>Link</u>
Synchronization policy	<u>Link</u>
Sync Signal Propagation	<u>Link</u>
Sending Model Parameters	<u>Link</u>
Validating Model Parameters	<u>Link</u>
Releasing New Model	<u>Link</u>
Reflecting model update in frontend	<u>Link</u>
	When period is 0 and the scheme is synchronous When spot at version is left null or is filled with float value Force Terminating System Synchronization policy Sync Signal Propagation Sending Model Parameters Validating Model Parameters Releasing New Model

TEST CASES:

Case 1 (When Trainers and Validators are less than or equal to 0)



Input : Clients and checkers are <= 0

Output: Alert prompt appears if clients and checkers

are less than or equal to 0

Case 2 (When period is 0 and the scheme is synchronous)

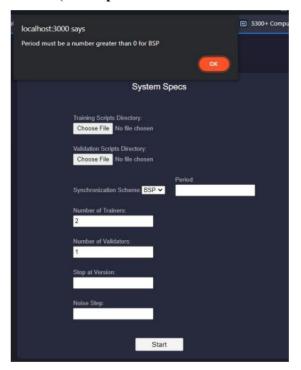


Figure 25.1. PROMPT ARAISES IF CONSTRAINTS ARE VIOLATED [BSP]

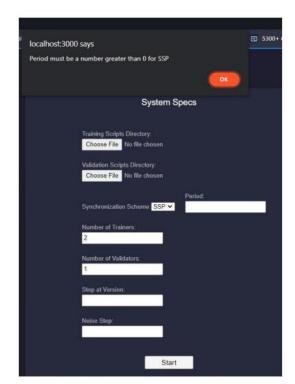


Figure 25.2. PROMPT ARAISES IF CONSTRAINTS ARE VIOLATED [SSP]

Input: Synchronous scheme and period is 0

Output: Alert prompt appears if period is 0 and scheme is synchronous

Case 3 (When spot at version is left null or is filled with float value)

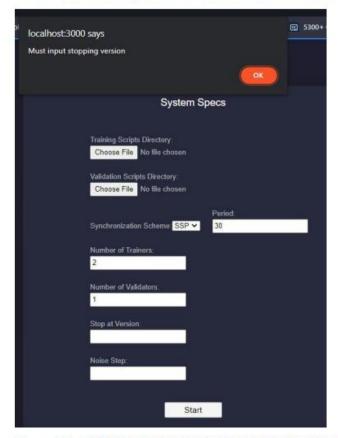


Figure 26.1. PROMPT ARAISES IF CONSTRAINTS ARE VIOLATED [VERSION CONTROL]

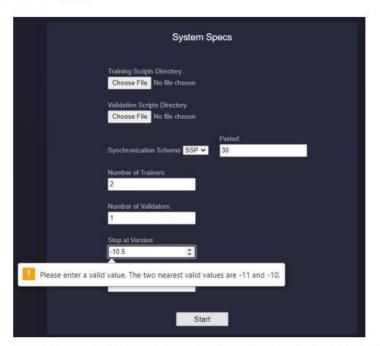


Figure 26.2. PROMPT ARAISES IF CONSTRAINTS ARE VIOLATED [VERSION

Input: Stop at version field is left null or filled with float value

Output: Alert prompt appears to rectify the stop at version field

Case 4 (Force Terminating System)

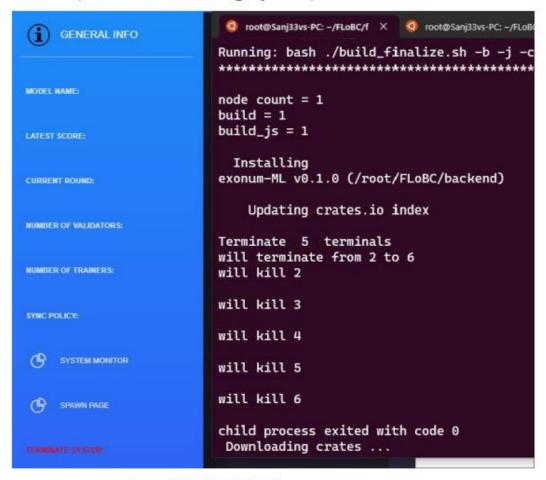


Figure 27. TERMINATING

Input: Fore kill framework instance signal sent to REST API

Output: The framework instance should kill and clear all the residues from blockchain

Case 5 (Synchronization policy)

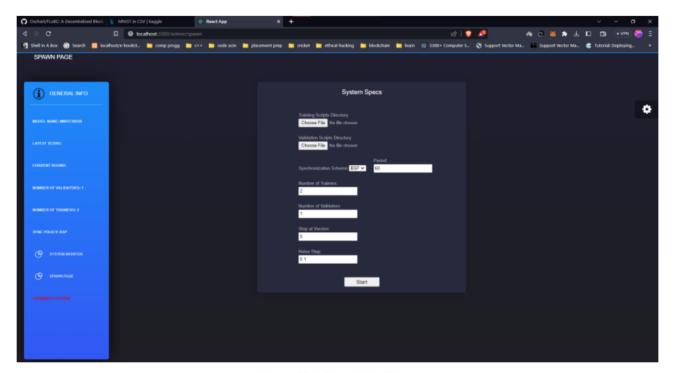
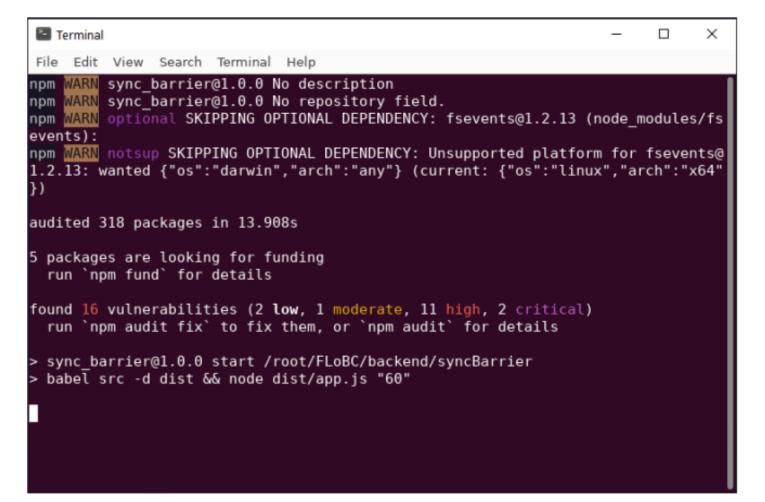
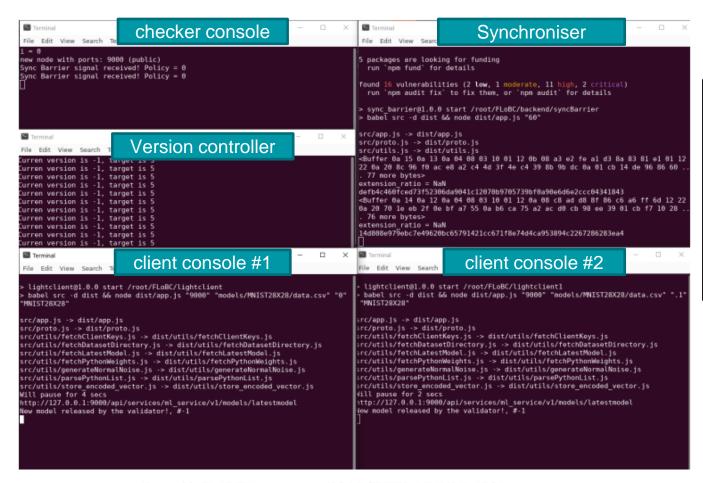


Figure 28.1. SPAWN PAGE

Input : Synchronization scheme chosen from the frontend dropdown Output : API correctly interprets the policy and spawns clients and checkers corresponding to the policy



Case 6 (Sync Signal Propagation)

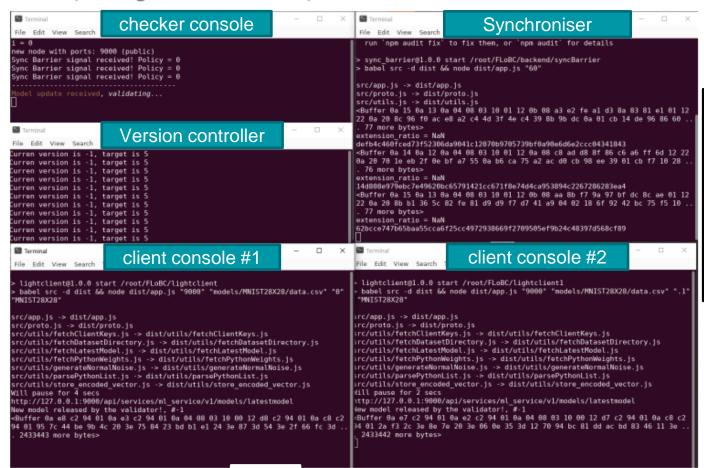


Input: Clients and checkers are created

Output: Clients and checkers communicate with each other and shares model updates

Figure 29. TRAINER

Case 7 (Sending Model Parameters)

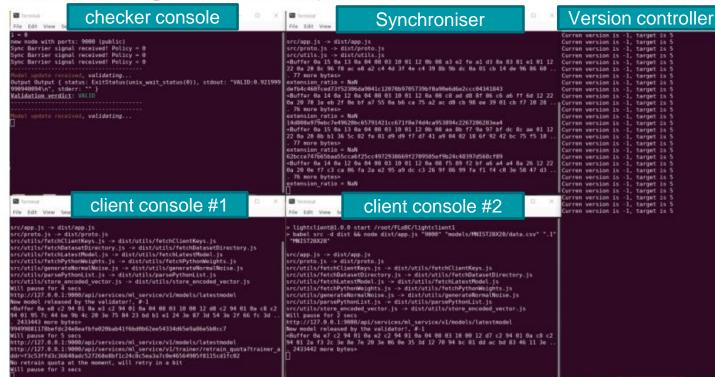


Input : Clients train the model with local dataset

Output: Trained model updates are shared to checkers

Figure 30. TRAINE. J MODEL PARAMETERS WITH VALIDATORS

Case 8 (Validating Model Parameters)

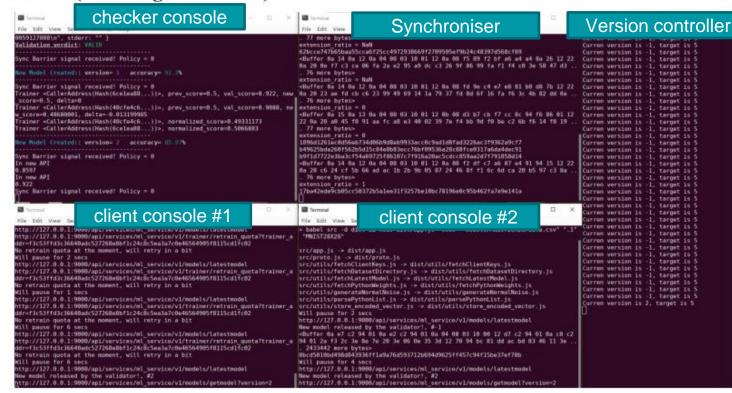


Input: All trainers shared their model updates

Output: A new model is released which aggregates the updates from all clients

Figure 31. VALIDATORS VALIDATING TRAINER MODELS

Case 9 (Releasing New Model)

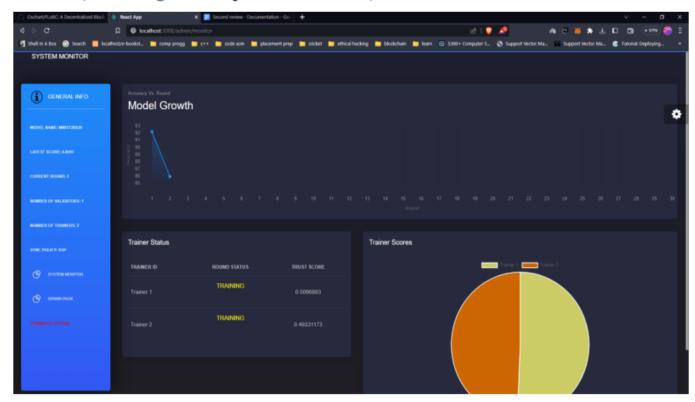


Input: New model is released by the checker

Output: All clients will receive the new model update from the checker

Figure 32. VALIDATORS RELESING THE NEW MODEL

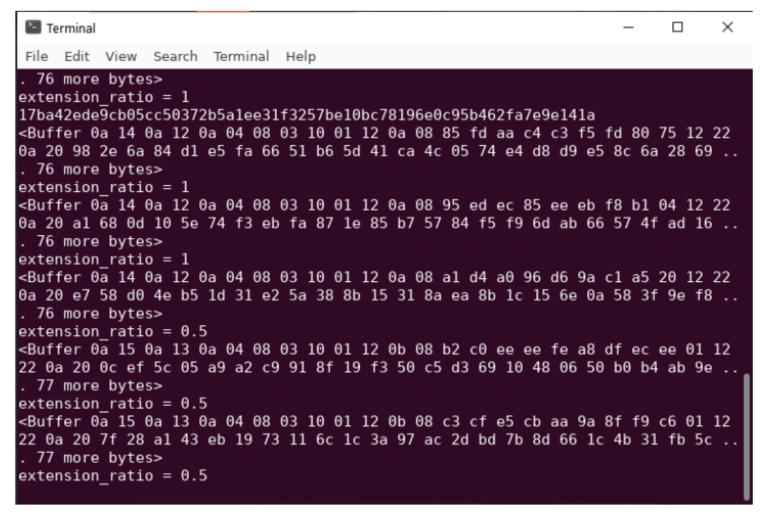
Case 10 (Reflecting model update in frontend)



Input: New model is released

Output: New model metadata is updated in the frontend and in its buffer

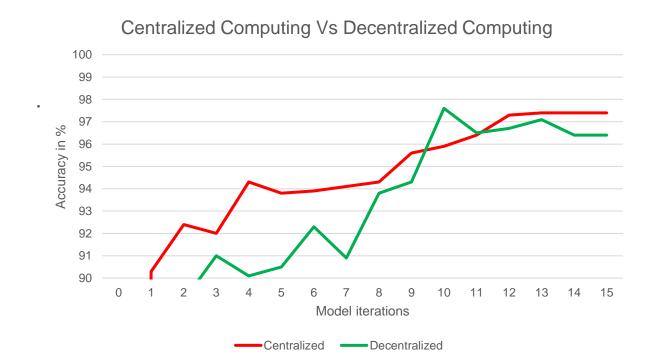
Figure 33. MODEL UPDATED IN FRONTEND



Benchmark: Decentralized vs. Centralized Performance

The purpose of this comparison is to check whether the security and privacy achieved from decentralized computing comes with a trade-off from loss of model quality and accuracy or whether model accuracy is unaffected by the advantages imposed by the decentralized model.

Benchmark: Decentralized vs. Centralized Performance



Benchmark: Decentralized vs. Centralized Performance

RESULT:

From the graph we can infer that with decentralized approach the model accuracy stays low as compared to centralized model for initial few numbers of iterations (6-7), it takes time to build up on the model accuracy as many decentralized actors would be contributing to build a model in each iteration with different datasets for them to train on. After initial few iterations we can infer that accuracy of centralized and decentralized model are in comparable with each other, and ends up with decentralized model having just 0.8% accuracy less than the centralized model. As for the benefits of security and privacy the decentralized model provides a very small percentage loss in accuracy is acceptable, also the trend can be subjected to change on different dataset or with more iterations where accuracy of both models would be similar.

clients-to-checkers Ratio

The purpose of this comparison is to check whether the difference in number of clients and checkers affects model accuracy, if so then we have to estimate the ratio of clients and checkers which would lead us to higher accuracy model as compared to others.

clients-to-checkers Ratio



clients-to-checkers Ratio

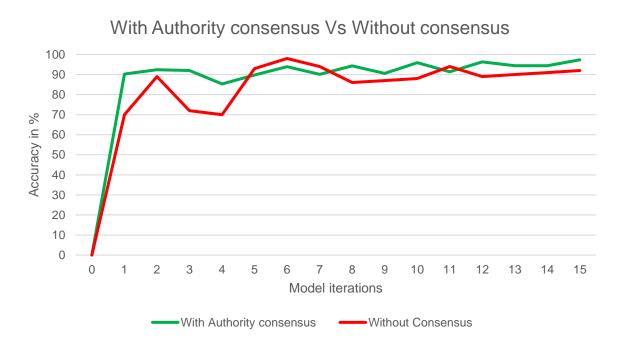
RESULT:

As we can infer from the graph lower number of clients has very ow accuracy, because they are trained on very low number of dataset rows, thus leading to lowest accuracy. And as the clients increases the model is trained on diverse number of dataset instances thus accuracy increases. And during 9 clients and 1 checker there is a bottleneck in checkers side as it cannot validate all 9 model instances which decreases the accuracy eventually. Thus Clients: Checkers ratio 8:2 should be maintained in order to achieve higher accuracy model with maximum utilization of available resources.

Authority consensus Policy

Another main component of D-FedL framework is Authority consensus which is responsible to make the overall system stable by avoiding model updates from the clients which constantly provides low quality model by penalising them and rewarding the clients with good quality model. The goal of the experiment is to compare the model growth with consensus and without it, and to infer whether usage of authority consensus increases model accuracy and stability.

Authority consensus Policy



Authority consensus Policy

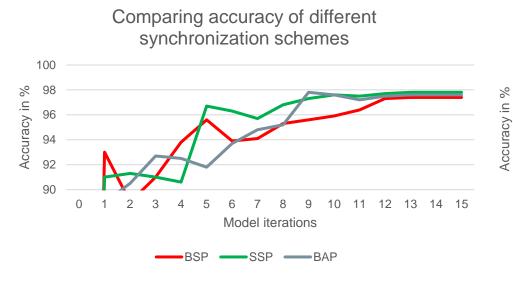
RESULT:

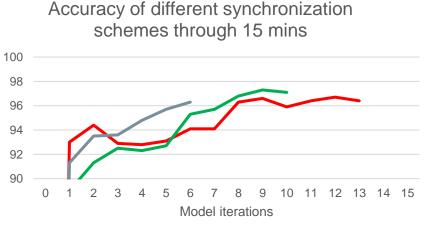
As we could infer from the graph, we could see large deviation in accuracy of the model trained without consensus, because nodes that provide low quality model would eventually bring down the accuracy of the model thus more fluctuation in model accuracy. Whereas on other hand model trained with authority consensus had very low deviation in the accuracy in successive rounds because it will stop receiving model updates from low performing nodes which increases model stability and model accuracy. After 15 rounds accuracy of the model trained with consensus came out to be 97.4% and the model without consensus was 91.9%, as we could notice the huge 5.5% difference in model accuracy between models trained with and without consensus. Thus using authority consensus seems to have improved model accuracy and stability.

Synchronization Schemes

In this experiment, we compare some of the common synchronization schemes used in parallel computing after adapting our own variations of them. The schemes implemented in DFedL and those tested in the experiment are Bulk Synchronous Parallel (BSP), Stale Synchronous Parallel (SSP), and Barrierless Asynchronous Parallel (BAP), as previously described in the methodology.

Synchronization Schemes





SSP BAP

Synchronization Schemes

RESULT:

- As we could infer from the graphs, at the end of 15 iterations the model accuracy of both synchronous and asynchronous schemes is almost same, but when we ran the system through particular time frame i.e) 15 minutes we could see BSP has higher number of iterations in 15 minutes but it has lower accuracy, followed by SSP which had completed 10 iterations in 15 minutes with higher accuracy and asynchronous scheme which has completed just 6 iterations.
- Though model accuracy is same at similar iteration, when it comes into the efficiency of using their resources synchronization schemes outperform asynchronous scheme by completing more iterations in fixed time frame.

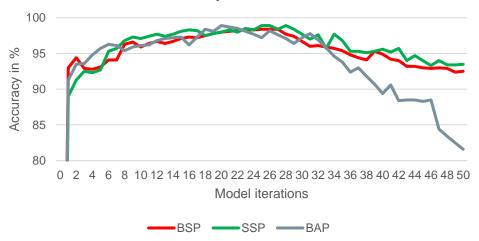
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Model Accuracy vs No of Iterations

• From this experiment, the goal is to find whether the highest number of iterations till which the model is not affected by overfitting which decreases the model accuracy and find which synchronization scheme is more susceptible to overfitting and to find the one which is least affected by it.

Model Accuracy vs No of Iterations





Synchronization scheme	Iteration number
BSP	25
SSP	26
BAP	22

Model Accuracy vs No of Iterations

RESULT:

• From the table and graph, we can infer that the maximum iterations we can train without model overfitting is 30, after which the model accuracy gradually decreases. Also, from the graph we could find that BAP model accuracy is drastically affected by overfitting, while BSP and SSP can withstand the model overfitting to a certain limit. The conclusion from the experiment is in order to avoid overfitting the threshold no of iterations is 30 and synchronous scheme seems to withstand overfitting to a certain margin..

CONCLUSION

- D-FedL is a proof-of-concept that demonstrates the ability of its constituent parts to work together to create a coherent system with the requisite levels of generality, decentralization, efficiency, privacy, and Byzantine fault-tolerance.
- The decentralized model has just 0.8% less accuracy than the centralized model.
- There is a quasi-optimal balance to be struck on client-to-checker partitioning, empirically establishing that an 8:2 client-to-checker ratio works well. Second, even a straightforward authority consensus approach may significantly improve the caliber of models that are created.
- Finally, three main synchronization systems (BSP, SSP, and BAP). SSP has been shown to be more economical than the other two approaches. Also, the maximum no of iterations that can run without overfitting is 30 iterations (threshold number), and BSP, SSP (synchronous schemes) can withstand overfitting to certain extent, but BAP (asynchronous scheme) found very vulnerable to overfitting.

FUTURE WORK

D-FedL may easily be modified to support additional computational models even though the SGD-compatibility of a model is an assumption built into the system. By giving the sync periods greater flexibility based on how long it is anticipated that most clients will take to submit their updates in a single round, synchronisation schemes can be further improved. Additionally, a layer of differential privacy might be added to transaction communication to restrict how far gradients can be inverted in order to extract client data, which would provide a better level of data privacy.

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