Federated Learning: Evaluating Popular Frameworks and Developing a Sever to Mimic Real Scenarios

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A Thesis Submitted in Partial Fulfilment of the requirements for the

Degree of

Master of Science in Data Analytics



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# Abstract

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# Abbreviations

|  |  |
| --- | --- |
| FL | Example of Abbreviation |
| AEA | Another Example Abbreviation |

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# Introduction

## Motivation

Within the domain of Data Analytics (DA), there is an important field known as Machine Learning (ML), which is embedded in everyday people's lives. A significant topic within this field is Federated Learning (FL). FL occurs when different devices collaborate to build a common model without exchanging their data; instead, the data remains on the devices, and only model updates are sent to a central server where aggregation occurs.

A good example for FL in everyday people’s lives is when phone users are typing a message, and the keyboard predicts words to complete the sentence, a model developed by Google engineers (Hard *et al.*, 2019).

A diagram of a phone system

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Figure 1.1. Illustration of a single FL communication round in FL for mobile keyboard prediction.

A different example where FL is helping society move forward is in the healthcare sector. Patients are using wearable devices to track their movements and help doctors monitor their health conditions (Arikumar *et al.*, 2022).

FL is growing rapidly and is helping the technological and medical sectors build robust machine learning models. This significant development motivates the focus of this thesis.

## Research Objectives

The primary purpose of this project is to experiment with FL frameworks to evaluate their implementability and develop a functional FL server. Therefore, the research objectives are:

* **To evaluate the implementability of existing FL frameworks.** This section experiments with popular FL frameworks, such as *PySyft, FATE, Flower, FedML* and *TensorFlow Federated* (TFF)*.* by examining their architecture and their applicability to real-world FL scenarios. This evaluation serves as the starting point for the primary research.
* **To develop a FL server**. A practical example of a web Flask FL server will be built, featuring two scenarios: technological and pharmaceutical. Each scenario will run separately, connecting five clients. Each scenario will have its own data, synthetic data for the technological scenario and images for the pharmaceutical scenario. These configurations will be trained, validated, and tested using Neural Networks (NN) that will classify binary outputs. This experiment aims to bridge the gap between popular FL frameworks and real-world FL applications.
* **To compare FL frameworks and the FL server.** This includes discussing the pros and cons each method brings to key industries such as the technological and pharmaceutical sectors. The comparison will focus on the following aspects ease of implementation, scalability, data privacy, and model performance.

## Thesis Overview

# Background

## What is Federated Learning

This concept was introduced in 2016 by Google engineer (McMahan *et al.*, 2016). FL is a shared model that is trained across multiple devices, often referred to as clients. Each client trains its own local model and sends the updates to a central server, where the updates are aggregated to improve the global model. It is important to note that clients do not exchange their data; the data remains private for each client. This principle drove the design of FL, following the concepts of *focused collection* or *data minimization*, which were introduced by the White House in 2013. The intent is to prevent personal data from being sent over the network and potentially being stolen or manipulated by malicious third parties.

## Federated Learning Classification Based on Client Nature

Depending on the nature of client FL can be classified in two types cross-device and cross-silo (Yang *et al.*, 2021).

### Cross-device

The clients for cross-device can be mobile devices, edge devices, Internet of Things (IoT) devices, smartphones, tablets, wearables, etc. Figure 2.2.1. illustrates this scenario.  
The characteristics are, the high number of participants it can be thousands to millions of devices, it may have limited processing power and battery life, datasets tend to be small and network bandwidth may be limited. Devices may also connect and disconnect intermittently.

A diagram of a computer network

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Figure 2.2.1. Cross-device scenario.

### Cross-silo

In this scenario, clients can be organizations or institutions such as hospitals, banks, and companies using large data centres. Figure 2.2.2 illustrates a cross-silo ecosystem. Some differences compared to the cross-device scenario include, clients are no longer small devices, there are fewer clients, clients have high computational power and large datasets, and the network is reliable with stable communication.

A diagram of a server

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Figure 2.2.2. Cross-silo scenario.

## Categorization of Federated Learning

FL can be categorized according to the distribution of the data held by the clients participating in the modelling. These categories help to understand the different methodologies and use cases for FL (Yang *et al.*, 2019).

### Horizontal Federated Learning

Horizontal Federated Learning (HFL) or sample-based FL, occurs when different clients have datasets that share the same feature space but differ in the samples they hold (see Figure 2.3.1). A practical example of HFL is when two hospitals in different regions each have patient records with the same features (e.g., age, height, weight, diagnosis) but for different patients. These hospitals can collaborate to train a model to predict disease outcomes without sharing patient data.

A diagram of a dataset

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Figure 2.3.1. Horizontal Federated Learning. Adapted from Yang et al., (2019).

### Vertical Federated Learning

Vertical Federated Learning (VFL), or feature-based FL, occurs when different clients have datasets that share the same sample IDs but differ in the feature space. An example of this is a bank and an e-commerce company that have data on the same set of customers. The bank has financial information such as credit scores and loan histories, while the e-commerce company has purchase behaviours and browsing records. By combining their data, they can build a model to predict customer credit without sharing raw data.

A diagram of a dataset

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Figure 2.3.2. Vertical Federated Learning. Adapted from Yang et al., (2019).

### Federated Transfer Learning

Federated Transfer Learning (FTL) is applicable when the datasets of different clients differ in both samples and features, and the overlap between both is minimal. To clarify, a good example is a European pharmaceutical company and a healthcare research institution in China collaborating using FTL. The pharmaceutical company has drug efficacy data, while the healthcare institution has patient health records. Even though they have different types of data, it is possible to train a global model to predict drug effectiveness on certain health conditions.

A diagram of dataset and dataset

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Figure 2.3.3. Federated Transfer Learning. Adapted from Yang et al., (2019).

## Federated Learning vs Distributed Machine Learning

Terms like FL and Distributed Machine Learning (DML) can create confusion due to their similarities. The main difference lies in the training process: in FL, there is a central server that aggregates updates sent by the clients, whereas in DML, there is no central server; instead, data is spread across different nodes and computations are shared among these nodes (Li *et al.*, 2020). Table 2.4 will help clarify the intricacies of each concept:

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Table 2.3.3. Differences between Federated Learning and Distributed Machine Learning

# Literature Review

## Federated Learning Frameworks

A requirement for selecting the FL frameworks was that they must be open source. Open-source frameworks are transparent and trustworthy, developed and maintained by a collaborative community, free to use, and constantly evolving. Additionally, they can be customized to meet users' specific needs. After the selection it was necessary to rank the frameworks. To accomplish this GitHub stats were helpful. Figure 3.1. depicts *PySyft* GitHub repository stats.

A screenshot of a social media post

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Figure 3.1. PySyft GitHub stats (OpenMined, 2019).

Contributors, forks and stars were counted for each framework. These stats were then normalised and finally averaged. Figure 3.2. illustrates the formulas and table 3.1. shows the results being *PySyft* the most popular open-source FL framework.

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Figure 3.2. Formulas for normalised stats and average.

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Table 3.1. Federated Learning frameworks by stats and ranking.

By creating this ranking, the population for objective one was defined as *PySyft, FATE, Flower, FedML,* and *TFF*. The population was restricted to the top five FL frameworks due to the limited amount of time. As the sampling method is non-probabilistic and the sampling type is judgmental, this approach to ranking the FL frameworks may help mitigate the inherent bias that experimentation has as a primary research methodology and also focus the selection on samples that can represent the entire population.

### PySyft, FATE, Flower FedML and TensorFlow Federated

Ziller *et al.*, (2021) introduced *PySyft* a multi-language library that facilitates secure and private ML. It was developed by the *OpenMined* community with the objective of making FL data science more accessible through Python bindings and user-friendly interfaces. *PySyft* uses libraries like *PyTorch* and TensorFlow with additional capabilities. Comparing it with other frameworks like *TFF* and *PaddleFL*; *PySyft* offers detailed building blocks, allowing developers to implement FL efficiently. Also compared to Flower that supports heterogeneous client environments and offers tools for mobile and edge devices, claiming and advantage over *PySyft* in these aspects.

According to Liu *et al.*, (2021) FATE is provided to aid enterprises and institutions in implementing large-scale and distributed collaborative learning with data protection. A number of secure computation protocols and machine learning algorithms are supported within FATE. Through the out-of-box usability and end-to-end building modules and visualization tools, users are able to get their applications up and running with efficiency and effectiveness. It not only offers a distributed platform that supports both stand-alone and cluster deployment but also privacy-preserving *XGBoost*, federated transfer learning, and multi-variate data. *FATE* interacts with users using *FATE-FLow*, which serves as the scheduling system, *FATE-Board*, a visualization tool, and *FATE-Serving*, which is an inference high-performance serving engine. *KubeFATE* is designed by *VMware* to have *FATE* constructed over *Kubernetes* at the data centre, hence an enterprise-managed solution over organizations' distributed infrastructure. It also supports cross-cloud deployment and management through *FATE-cloud*. Second, *FATE* has a security definition in which all parties are honest-but-curious, ensuring that the server learns only aggregated parameters, but not the data of any individual. It guarantees performance that is lossless, which means the algorithms in *FATE* provide comparable accuracy to a centralized solution. *FATE* supports research into the industry communities working together and has been seen as an increasingly business application of interest. Future work in the field will focus on the integration of blockchain functionalities into *FATE*; building lightweight versions of *FATE* for edge deployment and applications; and building new applications using *FATE* in an industrial scenario, such as computer vision and automatic speech recognition.

Also, Beutel *et al.*, (2022) presented a user-friendly framework, *Flower*, an open-source framework designed to enhance the capabilities and practical implementation of FL, across different environments. *Flower* addresses the challenges associated with the deployment and scalability of FL. Flower architecture allows simulations in real-world scenarios, making it a great tool for federated learning scenarios. The framework is agnostic supporting different machine frameworks like *TensorFlow* and *PyTorch*. Comparing Flower to other federating learning frameworks such as *TFF*, *PySyft*, *FedScale*, and *LEAF*. Flower stands out by supporting actual deployment on real devices rather than just simulation, unlike *TFF* and *LEAF*, which mainly focus on simulated environments.

Solanki *et al.,* (2022) delve into how *TFF*, an open-source framework, is utilized for machine learning on decentralized data. It has been designed for research and experimentation. Some of the key features are TFF enables FL through low-latency models with less power consumption. The framework uses two layers, the FL learning Application Programming Interface (API) and the federated core (FC) API. The FL API allows developers to implement training and evaluation on existing TensorFlow models through a high-level interface. The FC API integrates TensorFlow with distributed communication operators focusing on computations across distributed systems like mobile phones, tablets, and sensors. Comparing *TFF* to other frameworks, it offers a unique well integrated structure others do not provide this level of integration. *TFF* allows experimenting with new algorithms is not tied to predefined algorithms.

### OpenFL, NVIDIA, PaddleFL, Substra and FLGo

Another innovative framework OpenFL (Reina *et al.*, 2022)created by Intel Labs and the University of Pennsylvania, OpenFL supports decentralized machine learning models. It allows organizations to train models using data locally without any transfer, and that operates by distributing a global model across various nodes while each organization trains its model locally. Model updates are sent to an aggregator to enhance the global model. This framework is compatible with popular ML frameworks like TensorFlow and PyTorch. In comparison to other frameworks, it stands out due to its open-source nature, TensorFlow Federated or PySyft focus more on academic research applications while OpenFL is focused on real-world applications.

Wang *et al.*, (2023) developed *FLGo* a platform designed to streamline the process of cross-application FL research and enhance shareability among developers. It is a lightweight FL framework aiming to be a customizable solution to suit different applications and data heterogeneity. *FLGo* addresses the gap that exists in current FL frameworks which often make the FL deployment very complex. Some of the key Features, are benchmarks and algorithms, customization, experimental tools, and high degree of shareability. Compared to other frameworks it stands out in, system heterogeneity, high-level API, multi-architecture support, asynchronous operations and customization and flexibility. As a conclusion *FLGo* has been developed with the intention of making FL more accessible to a broader range of developers by simplifying customization and enhancing its shareability. It also aims to bridge the existing gap with conventional machine learning and FL.

### Federated Learning Algorithms

## Distributed Machine Learning

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## Federated Learning Server Implementation

## Federated Learning Datasets

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## Real World Federated Learning Scenarios

## Conclusion

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Identification of gaps

# State of the Art

# Research Methodology

## Methodology Frameworks

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## Project Management Framework

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## Business Requirements

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## Data Synthetic and Medical

## Data Preparation

## Limitations and Ethical Considerations

# Data Analysis

## Data Collection

## Initial Data Extraction and Exploration

### Data Elaboration

### Data Elaboration 2

## Conclusion

# Data Preparation

## Data Cleaning

### AAAAA

# Experimentation

## BBBB Option

## CCCC Option

## Aaaaaa Option

## BBBB Option

### CCCCC Option

# Validation of the Experimentation’s Results

## Validation BBBB

# Research Conclusion: Summary, Limitations, and Recommendations

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