Porting FedPSO to Flower; Benchmarking and Optimisation*

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***Abstract*—Federated Learning is a relatively new area of Machine Learning with many applications and vast potential.This method does not collect data on the server but instead proceeds with data directly from distributed clients.The challenges that accompany FL methods are network costs, computation cost, diverse hardware capabilities and development of algorithms that can best represent the learning of different clients.**

We are working on porting an algorithm, FedPSO to the Flower framework. FedPSO relies on Particle Swarm Optimization to converge the model. This algorithm increases robustness in unstable network environments by transmitting score values rather than large weights.

Importing to Flower allows scenarios to be simulated to analyze important metrics while also enabling FL methods to be used on hardware boards like Nvidia Jetson and Raspberry Pi.

As an additional objective we will be modifying the model to work with time-series data.

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Federated learning (FL) is an emerging paradigm in distributed machine learning where data is kept on devices (clients) and models are trained collaboratively without centralizing the data. This approach is particularly advantageous in scenarios where privacy concerns, bandwidth limitations, or legal restrictions prevent the sharing of raw data across multiple devices. FL has gained significant attention in areas like healthcare, finance, and Internet of Things (IoT) applications, where sensitive data resides on devices spread across diverse environments.

One of the key challenges of federated learning lies in its deployment across heterogeneous devices, which include smartphones, edge devices, and embedded systems. These devices differ greatly in terms of computational power, memory, and communication capabilities. This heterogeneity introduces obstacles to achieving high performance and scalability. For example, high-end devices like modern smartphones may handle training tasks efficiently, while lower-end edge devices may struggle due to limited resources. Therefore, optimizing federated learning algorithms to adapt to such a diverse environment is crucial for the success of distributed learning systems.

In this project, we aim to address the challenge of heterogeneity in federated learning by implementing a Particle Swarm Optimization based federated learning algorithm, FedPSO, using the Flower framework. Flower is a popular federated learning framework that provides flexibility in integrating various machine learning models and communication protocols across different devices. FedPSO leverages Particle Swarm Optimization (PSO), an evolutionary algorithm inspired by the social behavior of birds, to optimize model parameters during federated learning. Unlike traditional gradient-based methods such as FedAvg, which rely on gradient descent, FedPSO utilizes PSO to balance the learning workload across heterogeneous devices, making it more suitable for environments with varying computational capacities.

The primary goal of this work is to explore how the FedPSO algorithm can be effectively ported to devices with differing hardware specifications and resource constraints using Flower. We will investigate how the algorithm performs in terms of accuracy, communication overhead, and resource usage on a diverse set of devices. This research aims to contribute to the development of federated learning systems that are robust, scalable, and capable of running on devices with varying computational capabilities.

II. Problem Definition

A. *Maintaining the Integrity of the Specifications*

With the rise of IoT devices, there has been an explosive growth in the amount and diversity of data being generated.

From wearable health devices to smart home sensors, IoT devices collect vast amounts of real-time data across various domains. This distributed data is valuable for improving AI models, but centralizing it for training presents privacy and security concerns. Federated learning(FL) offers a solution by allowing model training to occur directly on devices, but it introduces significant challenges, particularly due to the limited computational capabilities of edge devices and the unstable network environments in which they operate.

FedPSO(Federated Particle Swarm Optimization) has emerged as a viable solution that addresses the aforementioned challenges. We will be implementing the FedPSO algorithm mentioned in [1] using the Flower framework. Further following the algorithm in [1], only the loss is sent back initially after which the weights of the of the client with minimum loss.This increases robustness in unstable networks.

III. Work Done

First the dataset is prepared for the client server setup.We have used the CIFAR 10 dataset to ensure uniformity across devices. Other the usual dataset transformations like converting to Tensor and normalization, it is also required to split the dataset to each client, a feature which is built into Flower.

Next we define a simple CNN for performing the image classification task.It is accompanied by a standard ”test” function as seen in other ML projects. Since we will be working with the weights directly, two methods get_parameters and set_parameters are required to interact with the model parameters. There are two major components in the Flower framework - the Client Class and the Server Class.

The Client has the *get_parameters*, *fit* and *evaluate* functions. There are three new attributes added to the client class to facilitate FedPSO - velocities, local_best_loss and local_best_parameters. The major differences in the client side are in the train function which uses Particle Swarm Optimization (PSO).The train function is further modified to return only the loss back to the server.

Moving on to the Server side, the major changes are required in the *configure_fit* and *aggregate_fit* function.We implemented three different algorithms,each one increasingly more accurate to the original pseudo code.

A. Prototype I

In each server round , the clients send back both the parameters and loss like most FL algorithms. The difference is that the parameters of only the best client is taken,set at the global best and sent back in the next iteration . The parameters sent by other clients are discarded and so this algorithm is inefficient.

B. Prototype II

The algorithm functioning is split into even and odd server rounds.In the odd server rounds the server contacts all the clients and the clients send back the loss. The client with best loss is found and in the next round(even) the server contacts only the best client and the client sends back its weights.This algorithm is the same as FedPSO except it will need twice the number of server rounds.

C. Prototype III

This implementation is the best representation of FedPSO.Clients send back loss from training , server finds the client with lowest loss and in the same server round makes a custom RPC call to the best client to get the best weights.

IV. Literature Survey

A. Communication-Efficient Learning of Deep Networks from Decentralized Data

Authors : Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, Blaise Aguera y Arcas.

In their seminal work on Federated Averaging (FedAvg), they have shown the potential to aggregate locally trained models without sharing private data as FedAvg trains high-quality models using relatively few rounds of communication by transferring weights to the server. While FedAvg has achieved success in various applications, it assumes that all participating devices possess comparable computational power and can communicate with the server reliably. In practice however, devices participating in FL are highly heterogeneous in terms of both computational capacity and network connectivity, posing challenges for efficient and equitable training.

B. FedPSO: Federated Learning Using Particle Swarm Optimization to Reduce Communication Costs

Authors : Sunghwan Park, Yeryoung Suh, Jeawoo Lee.

This study proposes the use of Particle Swarm Algorithm instead of FedAvg, this algorithm transfers score values rather than large weights. Thus significantly reducing the load on communication costs.

C. Boosted federated learning based on improved Particle Swarm Optimization for healthcare IoT devices

Authors : Essam H. Hussan, Awny Sayed

The Writers use a improved version of FedPSO called FedImpPSO to implement Federated learning on healthcare IoT devices. The FedImpPSO tackles problems like heteroginity of IoT’s such as ones with low computational power and low bandwidth, and Data Security and Privacy is maintained.

D. FLOWER: A friendly federated learning framework

Authors : Daniel J. Beutel, Taner Topal, Akhil Mathur, Xinchi Qiu, Javier Fernandez-Marques, Yan Gao, Lorenzo Sani, Kwing Hei Li, Titouan Parcollet, Pedro Porto Buarque de Gusmao, Nicholas D. Lane

This study presents Flower, a FL framework that supports large-cohort training and evaluation, both on real edge devices and on single-node or multi-node compute clusters. This unlocks scalable algorithmic research of realworld system conditions such as limited computational resources which are common for typical FL workloads.

V. Work Plan

Compare metrics with standard FL algorithms. Conduct real world test runs on devices like Raspberry Pi, Android and iOS. Further , modify the task to work on dynamic cab fare prediction. If time permits, work on another major challenge which is non - IID data.

References

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