Self Organizing Federated Learning Over Wireless Networks: A Socially Aware Clustering Approach

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***Abstract*—The significant proliferation of the Internet of Things (IoT) devices generates an enormous amount of data. Availability of such a large amount of data offers opportunities for using machine learning to enable intelligence in numerous applications. However, centralized machine learning schemes are based on migrating the data from devices to a centralized location for training. Such migration of data from user devices to a centralized location suffers from significant privacy concerns. To cope with this privacy preservation challenge, federated learning is a viable solution which enables learning in a distributed manner without migrating the data from devices to a centralized location. In this paper, we propose a novel federated learning scheme that offers federated learning without using centralized cloud server. First, we present a clustering algorithm based on social awareness which is followed by cluster head selection. Second, we formulate an optimization problem to minimize global federated learning time. Due to the NP-hard nature of the formulated optimization problem, we propose a heuristic algorithm to optimize the global federated learning time. Finally, we present numerical results to validate our proposed algorithm.**

***Index Terms*—Federated learning, device to device communication, machine learning, resource optimization.**

I. Introduction

The significant proliferation of the Internet of Things (IoT) devices in the last few decades have been witnessed. These IoT devices generate a significant amount of data that can be used to enable machine learning. Traditional machine learning schemes require migrating data from local devices to a centralized cloud for training. However, shifting the data from local devices to a centralized cloud poses serious privacy concerns. Federated learning is an emerging machine learning scheme that enables learning without the need to transfer data from local devices to a centralized cloud and thus, preserve the user privacy [1]–[3]. Federated Learning has shown distributed learning perspective rather collecting the whole data sets from a user. It enables devices to train the model based on local data to preserve the privacy of the users. The global model is updated iteratively by collecting the local model updates from the devices. Then, the central device will feedback the global model updates to the users. Based on the information of the central device, the local devices will update their models. This iterative process works until the convergence to some global federated learning model accuracy.

A. Motivation

Although federated learning offers a striking feature of privacy preservation. However, it suffers mainly from two prominent challenges:

- Malfunctioning of a centralized server at a cloud/edge server due to a physical damage results in failure of the federated learning process.
- A set of users involved in the federated learning process might not be able to access the centralized cloud/edge server due to lack of communication resources.

To cope with the above-discussed challenges, the set of densely populated devices can form a cluster which is subsequently followed by cluster head selection (central device) to enable self-organizing federated learning. The cluster head must be selected based on some key parameters: long battery life, better connectivity with other devices, and more computational resources. The cluster head acts as a central device/ server and carries out the global model aggregation of the federated learning process.

B. Use Case

Consider the scenario of smart tourism which consists of users with smart devices visiting a historical site. Every user want to get some best documentary of the visited historical site for getting more information. Other than that, few users want to add their own videos regarding the visited site. Enabling of most watched videos keyword suggestion at the users devices is possible via federated learning similar to keyboard words suggestion [4], [5]. On the other hand, federated learning requires significant communication resources for training because of the exchange of learning model updates between the devices. In [6], the concept of hierarchical federated learning has been presented. Similarly, we can train local devices via federated learning using only local devices cluster. Subsequently, the central node of a cluster (described in more detail later in the paper) will share the model with the remote cloud when the communication resources are available. The

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central node will resend back the globally trained model to the devices.

C. Related Works

Generally, federated learning has three main design aspects [7]: learning algorithm design [8], computation and communication resource optimization [9], and incentive mechanism design [10]. Our focus in this paper is resource optimization in federated learning. Numerous papers [9], [11], [12] considered resource optimization in federated learning. In [9], Tran *et al.* considered federated learning over wireless networks to enable two trade-offs: computation versus communication time and learning time versus energy consumption. The authors formulated the problem to optimize energy consumption and global federated learning time. Due to the non-convex nature of the formulated problem, it is decomposed into three sub-problems which are then solved using different algorithms. Another study in [11] proposed a control algorithm that enables trade-off between global parameter aggregation and local model update for minimizing loss function under resource budget constraints. To evaluate the performance of the proposed scheme, experiments based on real-time datasets have been conducted. On the other hand, Wang *et al.* [12] reviewed intelligence at edge networks via federated learning. A framework *In-Edge-AI* has been proposed for enabling intelligent resource management at the edge using federated learning. The authors tested their proposed framework through experimentation and finally, provided several open research challenges. All of the above-discussed papers considered a centralized server located at base station (BS) along with devices to carry out the federated learning process. However, none of the proposals considered self-organizing federated over wireless networks. Self-Organizing federated learning offers to learn without the need for central BS.

D. Contributions

This paper has the following contributions:

- First, we present a novel system model that enables federated learning without a centralized edge/cloud server.
- Second, we propose a clustering based on social relationship between devices. The central device (cluster head) is selected considering both social relationship and computational capacity of the node.
- Third, we formulate an optimization problem that aims to minimize the global federated learning time, while considering devices energy and communication resources constraints.
- Fourth, we propose a heuristic algorithm to enable Joint clustering and resource allocation for federated learning for minimizing the global federated learning model computation time.
- Finally, we provide numerical results to validate our proposed algorithm.

II. System Model and Problem Formulation

We consider the scenario of devices located in close vicinity and trying to train their local mobile models without

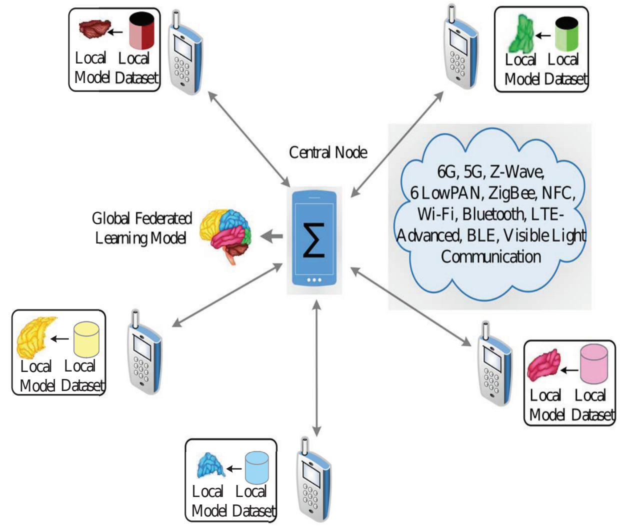

Fig. 1: Federated learning system model

using a centralized BS as shown in figure 1. Every device is specified by a social relationship with another device and a computational resource. To enable federated learning without using BS, it is necessary to choose one node as a central node that will perform global model aggregation. Therefore, we must select one device with sufficient computational resources and better social closeness with other devices as a central node. We first make a cluster of devices along with the central node which is then followed the learning process. We first present an overview of federated learning over wireless networks. Second, we discuss social-awareness based clustering. Finally, we formulate a problem to minimize the global federated learning time by selecting appropriate local devices frequencies and resource blocks for the exchange of local model updates over the wireless network.

A. Federated Learning over Wireless Networks

A set of devices $\mathcal{N}$ involved in federated learning having datasets with different sizes is considered. Every $n \in \mathcal{N}$ device has a dataset $\mathcal{D}_n$ with size D_n. The job of a device involved in learning is to perform local iterative scheme for computation of the local model weights w. These weights w characterize input to the output and its performance can be determined via local loss function $e_i(w) = \frac{1}{2}(x_i^T w_- y_i)^2$. Where x_i and y_i denote the i^{th} input and its corresponding output data sample, respectively. For a device n, the local loss function is given by:

$$J_n(w) := \frac{1}{D_n} \sum_{i \in \mathcal{D}_n} e_i(w). \tag{1}$$

In traditional federated learning, all devices involved in learning send their local model updates to a centralized server after computation of the local model updates. The centralized server performs local models aggregation of all the devices involved in learning. The global model parameters are then sent to local devices. This process of exchange of local updates and global model updates continue till convergence of global loss function to a desirable value.

$$\underset{w\in\mathbb{R}^d}{Minimize}\ J(w) := \frac{1}{D}\sum_{n=1}^{N_U} D_n J_n(w), \tag{2}$$

where $D = \sum_{n\in\mathcal{N}} D_n$. The goal of federated learning over a wireless network is to jointly optimize the global federated learning model accuracy, computational resources, and communication resources. The objective function $J(w)$ is assumed to be strongly convex in our paper and it has upper bound on global iterations which are given by [13]:

$$K(\epsilon,\theta) = \frac{O(\log(1/\epsilon))}{1-\theta}. \tag{3}$$

The upper bound of global iterations is determined by both local model accuracy θ and global model accuracy ϵ. We assume fixed global model and local model accuracy and normalize $(log(1/\epsilon))$ to 1 [9]. Therefore, (3) becomes $k(\theta) = \frac{1}{1-\theta}$. Next, we discuss socially and computational resource aware clustering.

B. Social Awareness

A social community is formed by a group of users having similar interests. The social relationship matrix of a device represents its social relationship with other nodes of its social community. In mobile networks, social community refers to a group of users having a similar background and frequent communication with each other. Social relationship in a mobile network is directly proportional to communication interaction between the corresponding users. Therefore, finding this communication interaction between the users offers the opportunity for resource allocation schemes to allocate more communication resources to socially close device-to-device pair for performance enhancement [14], [15].

In our system model, we consider the scenario which has no central BS. Therefore, to enable federated learning over such type networks, it is necessary to first find the node that will act as BS (i.e., central node). Numerous ways can be used to determine the central node that includes: nodes with more energy resources, a node with social centrality, and node with maximum computational resources. In our paper, we consider social centrality (more social closeness) as a selection criteria for the central node. The vector considering social closeness of n^{th} node with other M nodes is given by $\mathcal{S}_n = \{s_{n,m}\}_{1XM}$. Where $s_{n,m}$ has range of values between 0 and 1 for $n \neq m$ and 0 for $n = m$ [16]. Generally, the sizes of the local datasets of all the devices suffer from the striking challenge of unbalanced datasets sizes. On the other hand, every device needs to send its local model updates after a fixed amount of time in synchronous federated learning (considered in this paper). The time of local model computation significantly depends on local computational resources (CPU-cycles/sec) as well as local model accuracy.

C. Computation and Communication Model

Every n^{th} device involved in federated learning is specified by a running frequency $f_n \in \mathcal{F}$ and energy E_n. The frequency of every device is chosen from a set $\mathcal{F}$ which contains discrete frequencies randomly between $\{f_{min}, f_{max}\}$. All devices compute their local models which are then sent to a central device for global model aggregation. The local model parameters are sent to a central device for global model aggregation via the communication channel. The global model updates are then sent back to the devices after global model aggregation. We consider only up-link transmission delay due to the availability of low bandwidth compared to the high bandwidth of downlink. The transmission time of the downlink is negligible compared to up-link transmission time and therefore, we neglect it. An orthogonal frequency division multiple access (OFDMA) as an access scheme is used in this paper. A set of orthogonal resource blocks $\mathcal{R}$ is distributed among all the involved devices. The signal-to-noise-ratio (SNR) of a device n for resource block r with transmitted power P_n^r is given by:

$$\Gamma_n^r = \frac{p_n^r h_n^r}{\sigma^2}, \tag{4}$$

Where σ^2 and h_n^r denote the noise and gain between the n^{th} node and central node, respectively. In our model, we consider orthogonal resource blocks used by the devices and thus, there is no interference between the devices. Every resource block must be assigned to a maximum of one device.

$$\sum_{n\in\mathcal{N}} x_n^r \leq 1, \forall r \in \mathcal{R}. \tag{5}$$

On the other hand, a device can get a maximum number of resource blocks given by:

$$\sum_{r\in\mathcal{R}} x_n^r \leq r_{max}^n, \forall n \in \mathcal{N}. \tag{6}$$

The up-link achievable data rate for the device n is defined based on Shannon model as:

$$B_n^r = x_n^r W_n^r \log(1+\Gamma_n^r), \tag{7}$$

where W_n^r represents the bandwidth allocated to the device n for communication with the central node. The variable x_n^r is a binary variable which shows the association of a device n with resource block r ($x_i^r = 1$, if user i is associated with resource block r and vice versa). The up-link transmission time taken for sending of local model updates for the device n of size u_n bits is given by $t_n = \frac{u_n}{B_n^r}$. The global computation time of a single federated learning iteration does not depends on local model computation scheme as long as the convergence time is upper-bounded by $\mathcal{O}(\log(1/\theta))$ [9]. The computational time for one global iteration with local computation time t_{cmp} is given by $V\log(1/\theta)t_{cmp}$ [13]. The value of the constant V

depends on device data set size and it is taken equal to 1 in our system model. The total time taken by one federated learning global iteration is thus given by:

$$T_{global}(\boldsymbol{x}, \boldsymbol{f}) = \sum_{n \in \mathcal{N}} (t_n + log(1/\theta) t^n_{cmp}). \tag{8}$$

In this paper, we use a fixed global model accuracy. Therefore, the local device computation time strictly depends on device operating frequency, size of the local data sets, and local model accuracy. For a fixed local accuracy and data set size, the local device frequency determines the local computation time. The time taken by local device to process y_n bits and workload q_n (CPU-cycles/bit) with frequency f_n for one local iteration is given by:

$$t^n_{comp} = \frac{q_n y_n}{f_n}. \tag{9}$$

On the other hand, the choice of local device frequency determines the energy consumption and there is a direct relationship between them. Therefore, it is favorable to operate the device lowest possible frequency while fulfilling the other constraints. The energy consumed by the device n with CPU dependent constant parameter ρ running at f_n (CPU-cycles/sec) is given by $E_n = \rho_n y_n q_n f_n^2$. We assumed that the total energy consumed by all the devices involved in federated learning must not exceed the maximum energy limit.

$$\sum_{n \in \mathcal{N}} E_n \leq E_{max} \tag{10}$$

In our paper, we assume that all devices performs transmission with equal energy. We formulate our problem to minimize the global federated learning delay by optimal resource block allocation and local device frequency selection.

$$\mathbf{P1}: \underset{\boldsymbol{x}, \boldsymbol{f}}{\text{Minimize}} \quad T_{global}(\boldsymbol{x}, \boldsymbol{f}) \tag{11}$$

subject to:

$$\sum_{n \in \mathcal{N}} x^r_n \leq 1, \forall r \in \mathcal{R}, \tag{11a}$$

$$f_n \in \mathcal{F}, \forall n \in \mathcal{N}, \tag{11b}$$

$$\sum_{n \in \mathcal{N}} E_n \leq E_{max}, \tag{11c}$$

$$\sum_{r \in \mathcal{R}} x^r_n \leq r^n_{max}, \forall n \in \mathcal{N}, \tag{11d}$$

$$x^r_n = \{0, 1\}, \forall n \in \mathcal{N}, r \in \mathcal{R} \tag{11e}$$

The optimization problem 11 is to minimize the global federated learning model computation time by optimal selection of local devices operating frequencies and available orthogonal resource blocks. Constraint 11a restricts the assignment of one resource block to a maximum of one user. Constraint 11b restricts the selection of local device operating frequencies from a predefined discrete set of frequencies $\mathcal{F}$. The total energy consumed in the computation of the local model updates for all devices must not exceed the maximum allowed limited as indicated by 11c. The maximum number of resource blocks a particular device can get can not be greater than the maximum limit as indicated by the constraint 11d. Finally, the variable x^r_n can take only binary values and assigned value 1 if the resource block r is assigned to user n and vice versa. The optimization problem 11 is a Mixed-Integer Nonlinear Programming (MINLP) and NP-hard problem. To find a global optimum solution, we need to search the space of all feasible values of $f_n, \ \forall n \in \mathcal{N}$ with all possible values of the association variable $\boldsymbol{x}$ and this requires exponential complexity to solve. Therefore, we propose a heuristic algorithm to solve this optimization problem.

III. Proposed Self Organizing Federated Learning

Our proposed algorithm (presented in Algorithm 1) consists of two main phases: (a) cluster formation and (b) joint devices frequency selection and resource allocation. First of all the matrix $\mathcal{S}$ is used to find the central node (lines 4-5). The device having highest social relationship with other devices is chosen as a central node. Then, all the devices are assigned their lowest frequencies and their local model computation along with energies are computed (lines 6-8). After local operating frequencies assignment, all devices are assigned at least one resource blocks and local model computation time is computed. Lines(12-19) assigned devices having high computational latency with more resource blocks while fulfilling the constraint given in (6). All the devices are then sorted in descending order as per their global federated learning model computation delay (line 20). (Lines 21-26) performs the assignment of higher operating frequencies to the devices with higher transmission times and vice versa, while fulfilling the constraint of the maximum allowed the energy of all local devices computation. Finally, the overall global federated learning model computation time is computed (line 27). The above-explained algorithm works iteratively until the global federated learning model computation time converges.

IV. Numerical Results

This section presents the simulation results to evaluate the performance of our proposed algorithm. Simulation parameters are given in table I. We consider global federated learning time for one iteration in all results. For figure 2, we use $f_{min} = 300kHz$, $f_{max} = 500kHz$, and 110 resource blocks. The figure shows the global federated learning time versus different iterations of the proposed algorithm for a different number of devices. The figure 2 reveals the convergence of our proposed algorithm in several iterations (approximately 10 iterations). Furthermore, global federated learning time increases for an increase in the number of devices for fixed communication resources.

Figure 3 illustrates the average global federated learning time versus resource blocks. For this figure we use $f_{min} = 300kHz$, $f_{max} = 500kHz$, and $\gamma = 0.2$. We get all values of the global federated learning model computation time by taking the average of different values for 30 iterations. For less number of devices such as 40, average

Algorithm 1 Joint Clustering and Resource Allocation Algorithm for Federated Learning

Initialization
Local model accuracy θ, Global model accuracy ϵ, Local device frequencies set $\mathcal{F}$, Social relationship matrix $\mathcal{S}$, Constant α, Total resource blocks R, maximum resource blocks per device r^n_{max}.
Clustering
Select the central device based on S.
Cluster formation of the central device n with other m devices having social relationship $\{s_{n,m}\} \geq \gamma$.
Resource Allocation
Compute local devices computation time T_{comp} for their corresponding f_{min} frequencies using Eq. 9.
Arrange the devices in descending order as per local computation time.
Compute local device energy for all devices using $E_n = \rho_n y_n q_n f_n^2$.
repeat
    Assign R_N orthogonal resource blocks (one to each device)
    Compute the transmission delay using $t_n = \frac{u_n}{R^r_n}$
    $R_{rem} = (R - R_N)$
    for $n \leftarrow 1$ to N **do**
        if $(R_{rem} > 0)$ **then**
            Assign device n with $(r^n_{max} - 1)$ resource blocks.
            Update transmission delay t_n
            Update R_{rem}
        end if
    end for
    Sort the users in descending order according to T_{global}
    for $n \leftarrow 1$ to N **do**
        if $(\sum_{n \in \mathcal{N}} E_n \leq E_{max})$ **then**
            Next highest frequency assignment to n^{th} device.
            Update local computation time vector T_{comp}
        end if
    end for
    Compute $T_{global} = \sum_{n \in \mathcal{N}} (t_n + log(1/\theta) t^n_{cmp})$
    Arrange the devices in descending order as per values of T_{global}
until T_{global} converge

global federated learning time does not suffer from a clear decrease with an increase in a number of resource blocks. This is because we are having sufficient resource blocks to fulfill the communication needs of less devices. However, for higher number of devices the global federated learning model computation time is higher for lower number of resource blocks. On the other hand, if we consider the global federated learning time for higher values of resource blocks, the computation time is low with less difference for different number of devices. This is because of the presence of sufficient communication resource blocks.

TABLE I: Simulation Parameters [17]

Simulation Parameter	Value
Cell radius	100 m
Frame Structure	Type 1 (FDD)
Carrier frequency (f)	2 GHz
Devices transmit power	23 dBm
Sub carriers per resource block	12
Resource block bandwidth (W)	180 kHz
Thermal noise for 1 Hz at 20. C	-174 dBm
γ	0.2

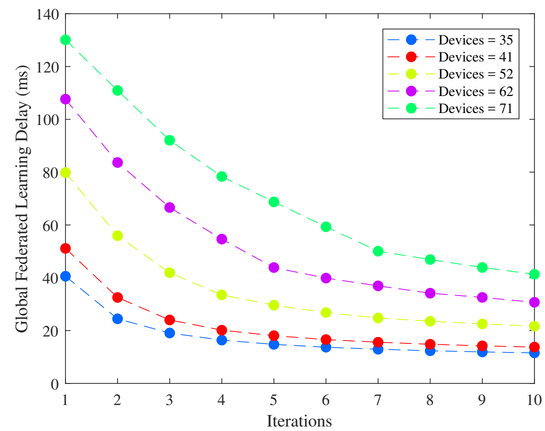

Fig. 2: Global federated learning time vs iterations

The effect of device operating frequency on the average global federated learning model is shown in figure 4. For this figure we use $\gamma = 0.2$ and 110 resource blocks. Similar to figure 4 all the values are computed by taking the average of different values in 30 iterations. It is clear from the figure 4 that with an increase in both low and high frequency of the local devices operating frequencies vector, the global federated learning computation time decreases. For higher number of devices the global federated learning time is higher due to communication resources constraints. It is clear from figure 3 and figure 4 that must be a trade-off between the local devices operating frequencies and communication resource blocks to enable efficient federated learning over wireless networks.

V. Conclusions and Future Recommendations

In this paper, we have presented a novel approach of self-organizing federated learning over wireless networks. We presented a heuristic algorithm to minimize the global federated learning time under the constraints of local devices energy consumption and resource blocks. We concluded several future recommendations from the paper:

- It is recommended to consider the distance of the central node from other nodes in its cluster formation in addition to social-awareness. This approach will further reduce the latency which in turn reduce global federated learning time. Moreover, this will offer a trade-off between the

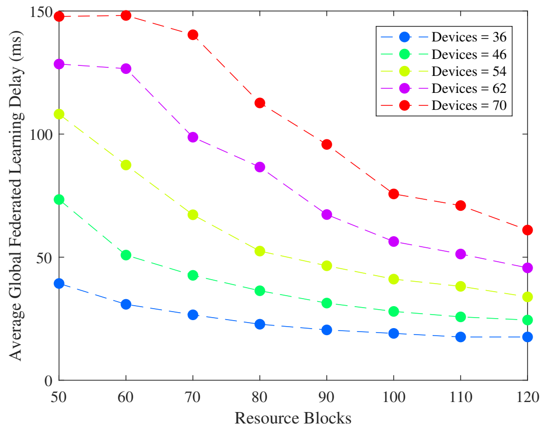

Fig. 3: Global federated learning time vs resource blocks

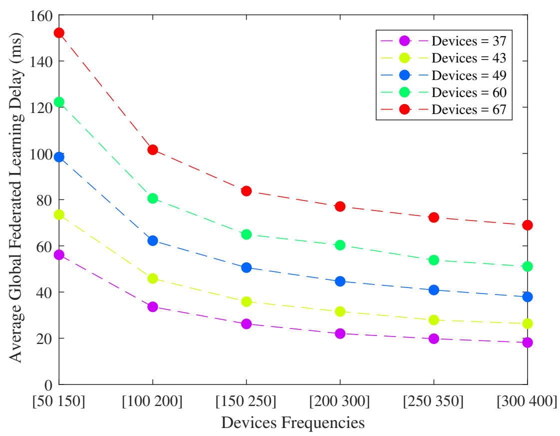

Fig. 4: Global federated learning time vs devices operating frequencies ($[f_{min}\ f_{max}]$)

social-awareness and distance between devices in the computation of the cluster.

- It is recommended to consider multiple clusters scenarios. Such type of multiple scenarios self-organizing federated learning is preferable for a massive number of devices within a densely populated area. Managing of a single cluster with a large number of users is difficult. Therefore, we can consider multiple clusters.
- It is recommended to propose new resource management and learning schemes for self-organizing federated learning for multiple clusters scenarios.

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