

Sub-channel Allocation in Federated Learning

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Abstract

Federated learning is a promising distributed learning technique, which can preserve the privacy of mobile users who join in the training model. However, during a global iteration, the mobile users need to send the local training model to the base station for update the global model. Therefore, the sub channels should be allocated so that minimize the delay cost and energy cost of users. In this paper, we apply the matching game for the sub-channel allocation. The simulation result shows that the proposed method is better than baseline.

model training.

1. Introduction

Mobile applications emerging with machine learning technology provides a great service experience to mobile users. In addition, the privacy protection of mobile users is a rising problem. Therefore, a distributed learning framework that allows devices to use individually collected data to train a learning model locally is developed. One of the most popular of such distributed learning framework is the so-called federated learning algorithm developed in [1].

In federated learning, mobile users can collaboratively train a global model while keeping all the training data on their own devices. In particular, a mobile user computes updates of the current global model on its local training data, which then aggregated and sends back to the central server. That process is repeated until an accuracy level of the learning model is reached [2].

The cost incurred due to participating the learning can make the mobile users be reluctant to participate the learning. In this paper, we consider the problem of sub-channel allocation for users to minimize the total cost. To solve problem we apply the matching game, which converge to the stable matching.

The rest of this paper is organized as follows. Section 2 describes the system model. Section 3 presents matching game. Section 4 provides the simulation results and Section 5 concludes the paper.

2. System Model

We consider a federated learning task consisting of one base station (BS) and a set of N users who participate in the federated learning task. Each user n has local training dataset of s_n local data samples. User n contributes f_n of CPU cycle frequency for local

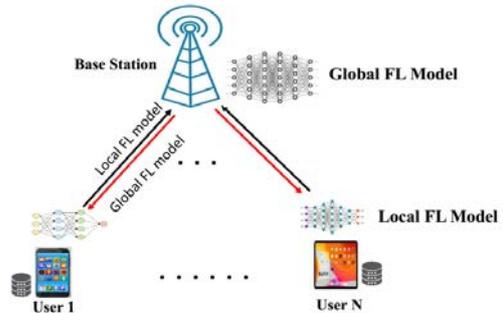


Fig. 1: System model

The number of CPU cycle to perform of one sample of data in local model training is denoted by c_n . Therefore, the computation time of a local iteration of user n is

$$T_n^{comp} = \frac{c_n s_n}{f_n}$$

For a federated training task, the users send their own local model updates to the BS through wireless links. Then the BS update the global model before sending a shared global model to users. This process is iterative until a global accuracy level of learning is achieved.

For the communication model, we consider that the BS has K subchannels, which are allocated to users for uplink the updating local model to the BS. If the subchannel k is allocated to user n , the transmission rate of user n is

$$r_n^k = W \log\left(1 + \frac{p_n h_{n,k}}{W N_0}\right),$$

Where W is the transmission bandwidth and p_n is the transmission power of user n . N_0 is the background noise. The transmission time of a local model update with the data size of σ is given as

$$T_{n,k}^{com} = \frac{\sigma}{r_n^k}.$$

The total time of one global iteration is

$$T_{n,k}^t = \log\left(\frac{1}{\varepsilon_n}\right)T_n^{comp} + T_{n,k}^{com}.$$

Where ε_n is the local accuracy of each local model update. The energy cost for transmitting local model updates in a global iteration is

$$E_{n,k}^{com} = T_{n,k}^{com} p_n = \frac{\sigma p_n}{r_n^k}.$$

The energy cost for one local iteration is

$$E_n^{com}(f_n) = \zeta c_n s_n f_n^2,$$

Therefore, the total energy consumption of the user n is

$$E_{n,k}^t = \log\left(\frac{1}{\varepsilon_n}\right)E_n^{comp} + E_{n,k}^{com}.$$

3. Matching game

The BS need to allocate the subchannels to the users to minimize the sum of energy cost and delay cost of the federated learning task. Therefore, we have the subchannel allocation problem as follows

$$\begin{aligned} \min_x \quad & \sum_{k,n} x_{n,k} (E_{k,n}^t + T_{k,n}^t) \\ \text{s.t.} \quad & \sum_k x_{n,k} \leq 1, \forall n \\ & \sum_n x_{n,k} \leq 1, \forall k \\ & x_{n,k} \in \{0, 1\} \end{aligned}$$

To solve this problem, we use matching game where users and subchannels are two sets of players. Each user constructs its preference list of subchannel with the utility function

$$E_{n,k}^t = \log\left(\frac{1}{\varepsilon_n}\right)E_n^{comp} + E_{n,k}^{com}.$$

Each subchannel builds its preference list of users with the utility function

$$T_{n,k}^t = \log\left(\frac{1}{\varepsilon_n}\right)T_n^{comp} + T_{n,k}^{com}.$$

In this paper, we assume that one user can be allocated one subchannel and one subchannel can be allocated to one user. Applying the deferred acceptance algorithm for the matching game with the quota of each player is 1. According to [3], this algorithm converges to the stable matching given fixed preference relations and fixed quotas.

4. Numerical Results

In this section, the simulation is conducted to evaluate the proposed trading

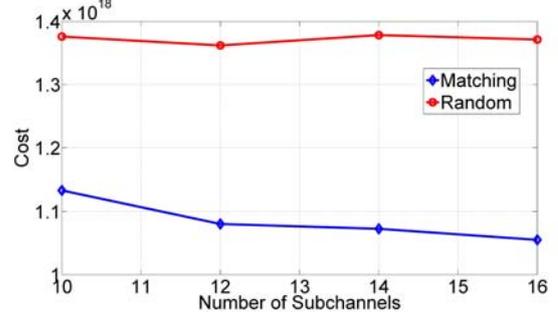


Fig. 2: Cost versus number of Suchannel

Fig. 2 shows that the proposed matching based allocation is much better than the random allocation. In addition, in the proposed allocation, when the number of subchannels increases, the cost decreases. This is because the user will choose the subchannels causing lower cost.

5. Conclusions

In this paper, we solve the problem of subchannel allocation in federated learning to minimize the total cost for users joining learning. The proposed method is applying the matching game with users and subchannels are two sets of players. Applying the deferred acceptance algorithm, the proposed allocation can save more cost compared with the random allocation.

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