Update and Channel Aware User Selection with Bandwidth Allocation for Federated Learning in Wireless Networks

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Abstract

Since the performance of the global model in Federated Learning (FL) is highly influenced by the participant users, the user selection has become a challenging approach. Due to the scarcity of wireless resources, it is impractical for all users to participate in FL. To improve the performance of the global model, the update of the local models is a critical parameter to take into account. In addition, the channel condition of the participant users should be considered to successfully decode the update of the local models. In this paper, we propose a user selection approach in which the selection of users is decided based on their updates and channel conditions. These parameters are assigned with a score which is controlled by the users. Moreover, the bandwidth allocation is determined based on the channel conditions where more bandwidth resources are allocated to the users with lower channel gains in order to minimize the time taken for one computation round.

1. Introduction

Federated Learning (FL) has become a prominent research topic since the privacy of users can be reserved by performing learning on the users' devices. Due to the imbalanced distribution of data at the users, the performance of the global model is affected by the local updates of the users. Since FL is implemented at the network edge, the wireless bandwidth allocation needs to be considered jointly with the training process.

The fundamental and challenges of FL model is surveyed in [1]. The one of the main challenges in FL is the joint user selection and resource allocation problem in wireless networks. Authors in [2] considered the user selection based on the packet error rate and bandwidth resources jointly. In [3], users with the higher update values and channel conditions are scheduled to participate in FL. Authors in [4] proposed a joint user scheduling and resource allocation problem to enhance the convergence of FL by solving the two problems alternatively. An age of update approach for the user selection problem is proposed in [5].

In this paper, we consider the user selection and resource allocation problem for FL in wireless networks. The user selection is determined based on two parameters, the update of the local model which is the distance between the global and local model, and the channel gain of the users. There is a trade-off between the global and local model with respect to the local update. If the local update is small, it would be beneficial for users since the computation for the next round would be less so that users can save their energy. When the local update is large, the global model receives the advantages by achieving the better model. Thus, users are allowed to control their own scores to the two parameters to balance the trade-off. In addition, a bandwidth allocation approach is proposed where users with the lower channel gains are assigned with the higher bandwidth to minimize the time taken for a computation round.

2. System Model and Problem Formulation

We consider a FL model in wireless network edge where users perform the local training on their devices and sends it to the base station to update the global model.

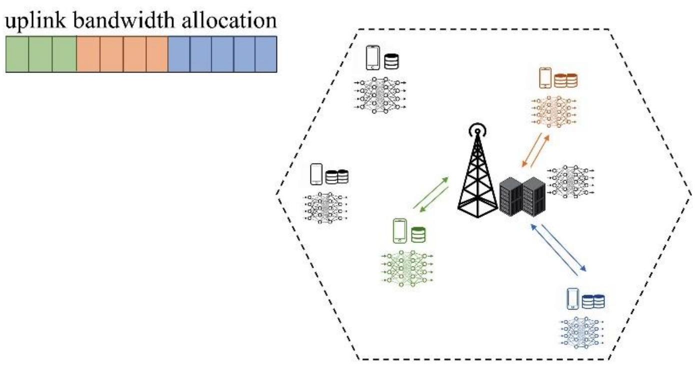

Figure 1. User Selection and Resource Allocation in FL

The Orthogonal Frequency Division Multiple Access is considered for uplink and transmission. The time taken to upload the current weight parameter from the local device to the base station is

$$t_i^{ul} = \frac{H(w_i)}{\beta_i B^{ul} \ \log_2(1 + \frac{p_i g_i}{n_0})}$$

where β_i is the fraction uplink bandwidth allocation, B^{ul} is the total available bandwidth, p_i is the user's transmit power, g_i is the uplink channel gain, n_0 is the additive white Gaussian noise and $H(w_i)$ is the size of the weight update. The total time taken for one communication round is

$$T_i = t_i^{ul} + t_i^p + t_i^{dl}$$

where t_i^p is the time taken for the local training and t_i^{dl} is the time taken for downloading the global model from the base station. We consider that t_i^p is varied according to the local update as there is a trade-off in energy consumption and the performance. In addition, t_i^{dl} is considered as a fixed value since the base station broadcasts the global model to all users. Thus, the joint training, user selection and bandwidth allocation for FL problem is formulated as follows.

$$\min_{w_i, \alpha_i, \beta_i} \frac{\sum_{i=1}^{U} \alpha_i \sum_{d=1}^{D_i} f(w_i, x_{ik}, y_{ik})}{\sum_{i=1}^{U} \alpha_i D_i}$$

s.t.

$$\max_i \{T_i\} \leq \tau,$$

$$\beta_i \leq \alpha_i, \forall i,$$

$$\textstyle\sum_{i=1}^{U} \beta_i \leq 1,$$

$$w_i \in \mathbb{R},\ \alpha_i \in \{0,1\}, \beta_i \geq 0,$$

where $f(w_i, x_{ik}, y_{ik})$ is the loss function. The objective is to minimize the loss of the global model. The first constraint ensures that the time taken for one computation round is bounded by a predefined threshold which is affected by the users with the maximum time. The second constraint makes sure that the bandwidth resources are not assigned to the users who are not participated in FL. The total available bandwidth resources are limited in the third constraint.

3. Update and Channel Aware User Selection

In this section, we propose an update and channel aware user selection for FL. First, we determine the candidate users based on their channel gains as follows.

$$\theta_i = \mathbb{I}\left\{\log_2\left(1 + \frac{p_i g_i}{n_0}\right) \geq \theta\right\}, \forall i.$$

This θ_i indicates that the user i is likely to be selected or not where its value is 0 or 1. Each user i declare its θ_i to the base station. The user selection is determined by the base station based on the update parameter and the candidate list as follows.

$$\alpha_i = \mathbb{I}\left\{\kappa_i \left[\frac{\Delta w_i}{\sum_{i=1}^{U} \Delta w_i}\right] + (1 - \kappa_i)\theta_i \geq \alpha\right\}, \forall i,$$

where $\Delta w_i = |\overline{w} - w_i|$ and $\overline{w}$ is the weight of the global model. Since w_i plays an trade-off between the global and local model, the decision of user i to participate in the FL is controlled by κ_i. If κ_i is large, user i is likely to participate in the FL without considering its energy consumption and channel conditions. If κ_i is small, the participation of user i is determined based on its channel condition. We define the set of the participating users as follows.

$$\mathcal{A} = \{i, \alpha_i > 0, \forall i\}.$$

4. Uplink Bandwidth Resource Allocation

In this section, the uplink bandwidth resource allocation is proposed based on the channel conditions of the users. According to the first constraint of the problem formulation in section 2, the time taken for one computation round is affected by the slowest user. Since $H(w_i)$ is similar in all users, t_i^{ul} is affected by the channel gain and bandwidth allocation of user i. Thus, we propose a bandwidth allocation approach where the more bandwidth resources are allocated to the users with lower channel gains. First, the participating user i declares its channel condition values to the base station as follows.

$$\gamma_i = \frac{1}{\log_2(1 + \frac{p_i g_i}{n_0})}, \forall i \in \mathcal{A}.$$

The base station assigns the uplink bandwidth to user i as follows.

$$\beta_i = 1 - \left[\frac{\gamma_i}{\sum_{i \in \mathcal{A}} \gamma_i}\right], \forall i \in \mathcal{A}.$$

5. Evaluation Results

A single cell wireless network model is considered where users are uniformly distributed within 1km radius. Transmit power of users is 20dbm. The size of the weight values follow the uniform distribution which is [300, 800] KB. The linear regression model is considered for the model training in FL where the training data is generated randomly. For the comparison, we perform four cases where all users are selected for the training, users are not willing to participate in the training $(\kappa = 0.3)$, users are neutral about the participation $(\kappa = 0.5)$ and users are likely to participate in the FL $(\kappa = 0.7)$.

Fig 2. shows the performance of the FL model where the four cases are compared with the optimal solution. When all users are participating in FL, the performance of the global model is close to the optimal solution since the global model receives the benefits from training the local data on all local models. One interesting result is that when users are neutral about the participating, more users are selected by the base station which results in the better performance of FL.

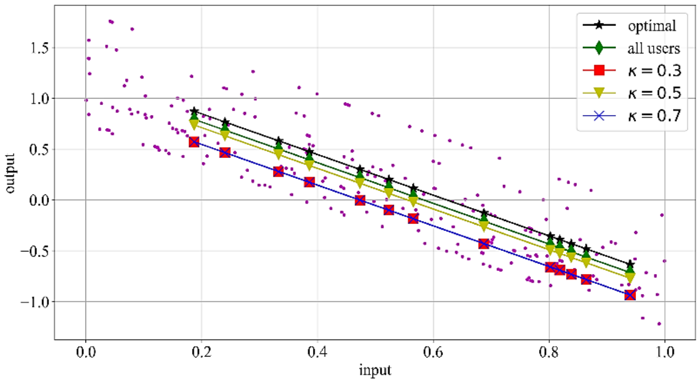

Figure 2. Performance of the FL model

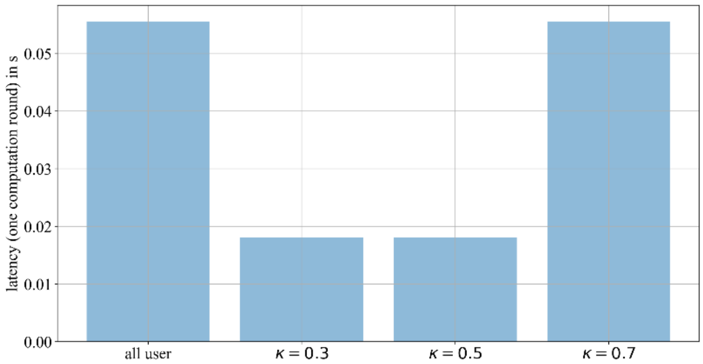

Figure 3. Latency taken for one computation round

The latency taken for one computation round is shown in fig. 3. When all users are participating in the FL, the available bandwidth has to be shared among all users which results in the higher latency. When most of the users are willing to participate in FL $(\kappa = 0.7)$, the selection decision is based on the weight parameter by ignoring the channel condition of users which also results in the higher latency.

6. Conclusion

In this paper, an update and channel aware user selection is proposed for the Federated Learning. The channel conditions of users are taken into account to make sure that the local updates are successfully decoded at the base station. Since the update plays an crucial role in trade-off between the global and local model, users are allowed to control its participating decisions by a parameter. In addition, the uplink bandwidth allocation is performed with respect to the channel conditions of the users in order to improve the time taken for one computation round. The simulation results show that the score parameters controlled by the users influence the performance of the system.

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