Incentive-Aware Autonomous Client Participation in Federated Learning

Background&Motivation

目前大多数的工作都假设所有的client都愿意参与每一轮的训练，并完全由集中式的PS决定采用哪些client的本地训练结果来更新全局模型。作者认为这一假设是不符合实际情况的，因为对于资源受限的设备，参与训练会产生一定的开销，比如算力，能量等，因此在实际场景中client不一定愿意参与训练。其次，即使没有资源限制，在某些场景如多个商业公司之间的联邦学习，各个client也希望在参与训练之后，获得一定回报。因此，在联邦学习中，引入对client奖励机制来激励client是很有必要的。而且，是否参与该轮训练应由client自己做出决策，即该client selection过程是分布式而且自治的，而不是中心式的。

一个很朴素的做法就是在每一训练轮中PS提供一定数量的奖励，每一个client会基于自己可以获得的收益(reward-cost)来做出是否参与本轮训练的决策，然后PS为参与本轮训练的client分配这一奖励。显然，参与的client越多，那么每个client获得的reward就越小，当reward不能够cover cost, 那么client就倾向于不参与本轮训练，反之。但这个问题的难点在于在联邦学习的场景中，出于对privacy的考虑，client是同时做决策的，client没法知道其他client的选择。

上述这个问题有点类似是client在做博弈，因此作者引入了 minority game(少数派博弈)这一博弈论模型来解决该问题。

System Model And Game Formulation

每个client会基于自己可能获得的效用来做决策，因此需要先定义效用(reward-cost)

Game Without Incentive From PS

model accuracy improvement

$$q(t) = Q(X(t)) - Q(X(t-1)), \tag{1}$$

where $X(t) = \sum_{k=1}^{t} \sum_{i=1}^{N} x_i(k)$ *is the cumulative number of mini-batches contributed until round* t.

FL public reward

$$R_i^{FL}(x_i(t), \mathbf{x}_{-i}(t)) = \gamma_{\text{client}}(X(t-1))q(t), \tag{2}$$

where $\mathbf{x}_{-i}(t)$ *is the number of mini-batches contributed by clients except client* i *at the training round* t, $X(t) = \sum_{k=1}^{t} \sum_{i=1}^{N} x_i(k)$, γ_{client} *is the marginal per capital return (MPCR) [32] from the perspective of clients, which can be set at the client's discretion.*

Unfortunately, the reward defined in Eq. (2) is hard to obtain in practical scenarios. Alternatively, we can approximate it by the following equation:

$$R_i^{FL}(x_i(t), \mathbf{x}_{-i}(t)) \approx \lambda_{\text{client}} \sum_{i=1}^{N} x_i(t), \tag{3}$$

$$\gamma_{\text{client}}(X(t-1))Q'(X(t-1)) \triangleq \lambda_{\text{client}}.$$

> 因为所有client都可以获得一致的全局模型，所有参与训练的client的FL public reward都是相同的，

cost

$$c_i(x_i(t)) = \eta x_i(t), \tag{4}$$

where η is the cost coefficient that can be obtained from field measurements.

> cost由通信成本和计算成本组成，通信成本由模型参数数量决定，一般对所有client都是一样且不变的，计算成本由数据量决定，每个样本的计算成本一样，因此成本是数据量的一个线性函数

utility

$$U_i(x_i, \mathbf{x}_{-i}) = R_i(x_i, \mathbf{x}_{-i}) - c_i(x_i). \tag{5}$$

The utility depends not only on client i's strategy x_i but also on strategies chosen by opponents $\mathbf{x}_{-i}$.

$$U_i(x_i, \mathbf{x}_{-i}) = \lambda_{\text{client}} \sum_{i=1}^{N} x_i - \eta x_i. \tag{6}$$

Specifically, we have the following two propositions on the Nash equilibrium of the formulated game.

Proposition 1. *When $\lambda_{\text{client}} \geq \eta$, the Nash equilibrium can be achieved when each client contributes all its data to FL training. That is, the strategy profile $\mathbf{x}^* = \{K_1, \ldots, K_N\}$ is a Nash equilibrium.*

Proof. The proof can be found in Appendix B, available in the online supplemental material. □

Proposition 2. *When $\lambda_{\text{client}} < \eta$, the Nash equilibrium can be achieved when each client contributes nothing to FL training. That is, the strategy profile $\mathbf{x}^* = \{0, \ldots, 0\}$ is a Nash equilibrium.*

Proof. The proof can be found in Appendix C, available in the online supplemental material. □

> 纳什均衡：Intuitively, a Nash equilibrium is a stable strategy profile: no client can gain higher utility by changing its strategy if the strategies of other clients are unchanged

当$\lambda_{client} \geq \eta$, 即cost比较小的情况，所有的client都会自主选择参与训练，而当$\lambda_{client} < \eta$ 时，所有client都会选择不参与训练。这表明仅靠public reward不足以激励client参与训练。因此需要引入额外的reward来激励client

Reward From PS

$$R_i^{PS}(x_i(t), \mathbf{x}_{-i}(t)) = \frac{Cx_i(t)}{\sum_{i=1}^{N} x_i(t)}, \tag{8}$$

where C is the total amount of credits allocated by the PS as the reward in each training round. In practice, the credit value can be determined by jointly considering the training cost and the number of required participating clients per training round.

$$R_i(x_i(t), \mathbf{x}_{-i}(t)) = \lambda_{\text{client}} \sum_{i=1}^{N} x_i(t) + \frac{Cx_i(t)}{\sum_{i=1}^{N} x_i(t)}. \tag{9}$$

Standard MG-Based Client Participation Decision Algorithm

Definition 6. Minority Game Model. *The properties of the minority game are given as below:*

- *There are N clients in the FL system.*
- *At each training round t, each client i makes a decision $a_i(t) \in \{+1, -1\}$. The action $a_i(t) = +1$ indicates that a client selects the "cooperated strategy", and $a_i(t) = -1$ indicates that a client selects the "defected strategy".*
- *The clients who are in the minority side, i.e., $a_i(t) = -\mathrm{sign}(\sum_{i=1}^{N} a_i(t))$, win, and the others lose.*
- *No communications between players are allowed.*

state

> In our model, the state of a client is defined based on its decision history and winning side information.

client不知道彼此的情况，仅知道过去的winning side information，即之前哪方是少数派(赢家)，1表示参与该轮训练的是少数派，-1表示不参与该轮训练的是少数派

TABLE 3
An Example State Transition for a Client

The state at FL training round t			The winning decision	The state at FL training round $t+1$		
1	-1	1	1	-1	1	1
1	-1	1	-1	-1	1	-1

utility

$$U_{i,t}(s,a) = U_{i,t-1}(s,a) - a_i(t)\frac{A(t)}{N}, \tag{13}$$

A(t) is Attendance at round t, which is the collective sum of the difference in the actions of all players at a given time t.

$$A(t) = N_+(t) - N_-(t) = 2N_+(t) - N.$$

因此，当A(t) < 0，表明参与训练的client是少数派，因此做出参与训练决策的client获得奖励，其他client获得惩罚。

Decision Strategy

$$a_i^*(t) = \arg\max_{a} \quad U_{i,t}(s,a). \tag{14}$$

$$\Pr\{a_i(t) = a\} = \frac{e^{\beta U_{i,t}(s,a)}}{\sum_{a' \in \mathcal{A}} e^{\beta U_{i,t}(s,a')}}, \tag{15}$$

algorithm

Algorithm 1. Standard MG-Based Client Participation Decision

Given: $N, a_i(t) \in \{+1, -1\}, C$
% Step 1: decision initialization
for $i = 1 : N$ **do**
    Randomly initialize decision for client i;
end for
repeat
    % Step 2: transaction
    The clients conduct local model update;
    PS calculates the attendance A following Eq. (11);
    PS sends rewards $C/N_+(t)$ to each cooperator;
    % Step 3: utility update
    % minority side determination
    if $A(t) > 0$ **then**
        $\mathrm{win}(t) = -1$
    else
    $\mathrm{win}(t) = +1$
    end if
    PS broadcasts the winner information $\mathrm{win}(t)$;
    for $i = 1 : N$ **do**
        % Update the utility function following Eq. (13);
        if $a_i(t) \neq \mathrm{win}(t)$ **then**
            if $(\mathrm{rand}()\%N) < \mathrm{abs}(A) - 1$ **then**
                $a_i(t+1) = (a_i(t) + 1)\%2$
            end if
        end if
    end for
    $t = t + 1$
    % Step 4: decision iteration
    Clients act following the probability in Eq. (15);
until PS claims that the training process ends.

Improvements

上述Standard MG-Based的算法存在的问题是系统的Volatility波动较大，不利于模型收敛

> Basically, the attendance value never settles but fluctuates around the mean attendance (i.e., cut-off value). The fluctuation around the mean attendance is known as volatility

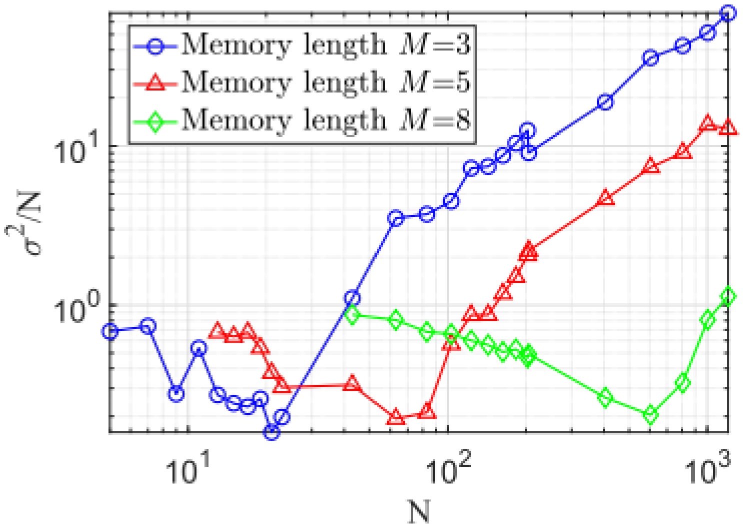


Fig. 3. The volatility per client versus the number of clients in the FL system.

因此，文章进一步又提出来俩种改进算法，从而降低volatility

Stochastic MG-Based Client Participation Decision Algorithm

The process is as follows:

- If a client i is successful in a given round, it will make the same decision in the next round: $a_i(t+1) = a_i(t)$.
- Otherwise, the client will change its action with a probability $p = \Pr\{a_i(t+1) = -a_i(t)\}$.

round t+1,上一轮的少数派继续坚持之前的策略，多数派以一定概率取相反的策略

Coalition MG-BaseD Client Participation Decision Algorithm

> Recall that there is no information sharing in both standard MG-based decision and stochastic MG-based decision algorithms. We then propose a coalition MG-based client participation decision algorithm by taking advantage of cooperation among some clients

每一个coalition中仅仅包含俩个client，且同一个coalition中的client总是选择相反的策略

Algorithm 2. Client Coalition Formation Algorithm

1: **Given**: $N, d_{i,j}, i, j \in \{1, \ldots, N\}, \mathcal{S} = \varnothing, \mathcal{R} = \mathcal{N} = \{1, \ldots, N\}$
2: **repeat**
3: Select the pairs i, j that minimize $d_{i,j}$;
4: $\mathcal{S} \leftarrow \mathcal{S} \cup \{i\} \cup \{j\}$;
5: $\mathcal{R} \leftarrow \mathcal{R}/\{i\}/\{j\}$;
6: Find the clients to be added into $\mathcal{S}$ following Eq. (26);
7: **until** $\mathcal{R} = \varnothing$ or $|\mathcal{R}| = 1$.

Evaluation

TABLE 4
Experimental Parameter Settings

Symbol	Definition	Default Value
N	the number of players/clients	1001
x	# of mini-batches per client	10
C	the recruitment budget per round	500
c	the parameter for stochastic MG	1,10
ψ	the cutoff value	50
M	the historical length	5
S	the size of strategy space	2
β	the weight for standard MG	1
η	the coefficient for cost function	1
T	the total number of training rounds	100

c是Stochastic MG中用的参数，c越大，表示越大的exploration probability

attendance

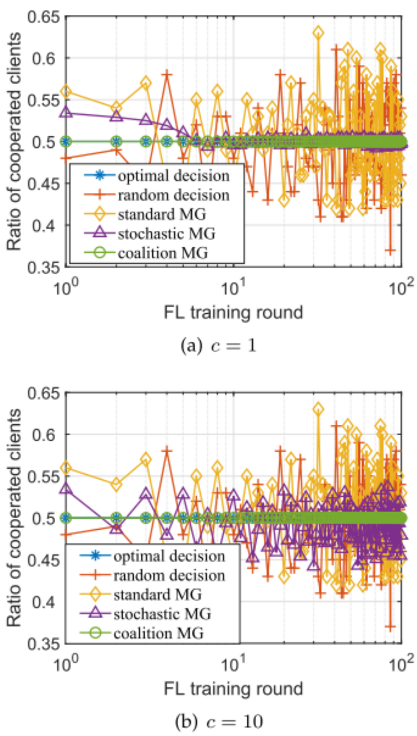


Fig. 7. The ratio of cooperated clients versus the FL training round.

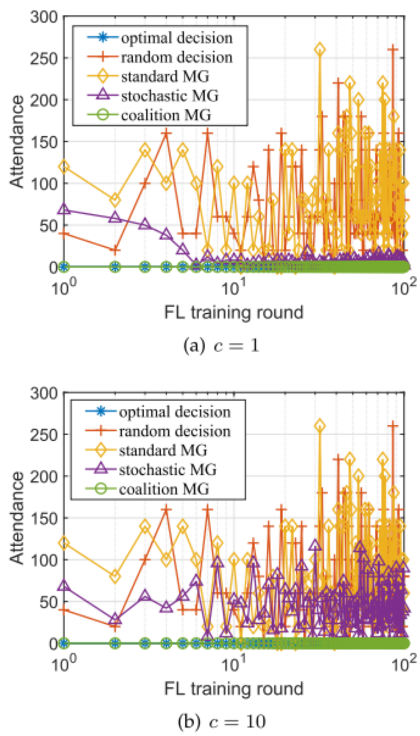


Fig. 8. The attendance versus the FL training round.

Volatility

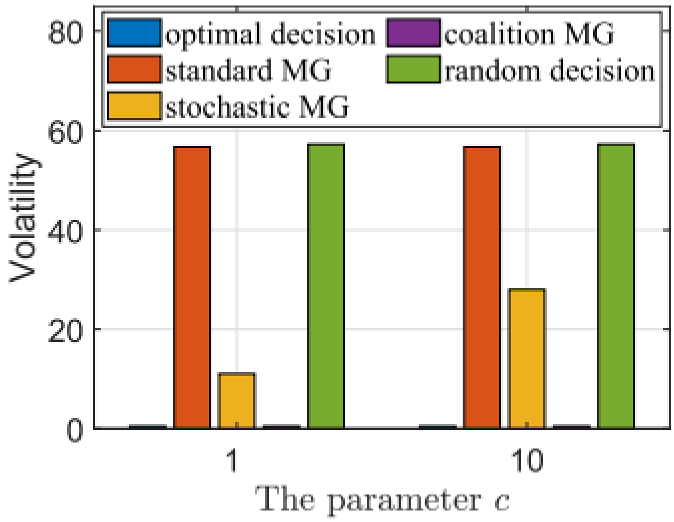
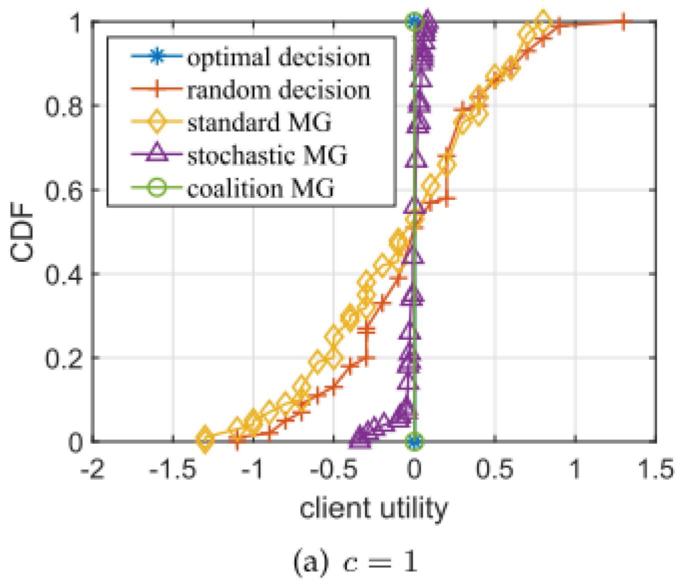


Fig. 9. The system volatility versus different parameter c.

Utility



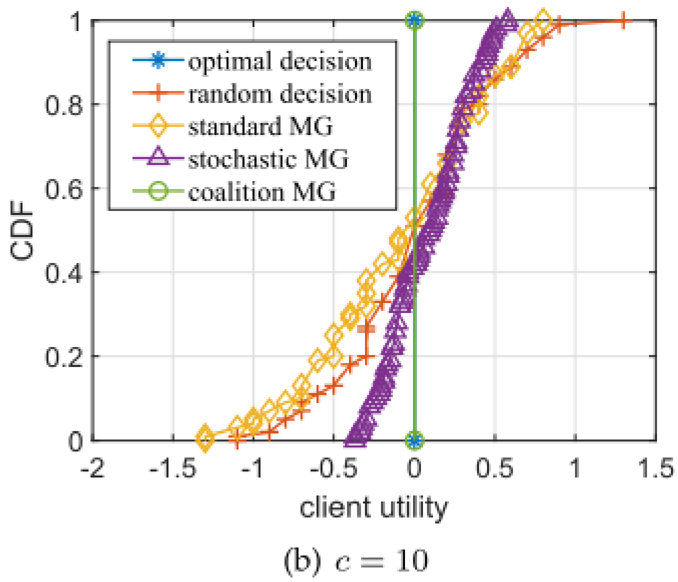


Fig. 10. The CDF of client utility over the FL training process.

Conclusion

The results indicate that the stochastic MG-based algorithm and the coalition MG-based algorithm can improve the utility by 39%-48% and reduce the volatility by 51%-100% compared to other baselines.

优缺点

优点

- 文章指出了之前工作假设不合理的地方，并基于一个更符合实际的场景进行client selection schema的设计
- 首次将博弈论中的少数派模型引入FL中进行client selection, 方法比较新颖

缺点

- 从完全中心式的client selection转为了完全自主的client selection, 每个client做出参与训练的决策，PS就一定要采用其结果，但不同的client是异构的，如算力，数据质量，我认为PS还是应该有一定决策权，选择能使全局模型最优(训练效率，模型准确度)的client

其他

Minority game (MG) [25] is a powerful theory tool in modeling collective behaviors of clients when they have to compete for limited resources with incomplete information.