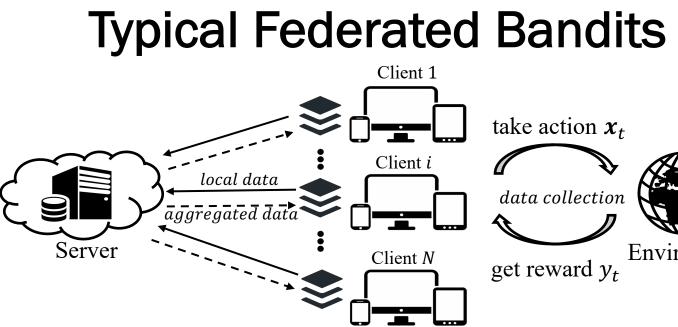
RGINIA

Motivation



For time t = 1, 2, ..., T

- For client i = 1, 2, ..., N
 - Client *i* takes action x_t from action set \mathcal{A}_t and observes **reward** $y_t = f(x_t) + \eta_t$

Environment

• Communication between server and clients

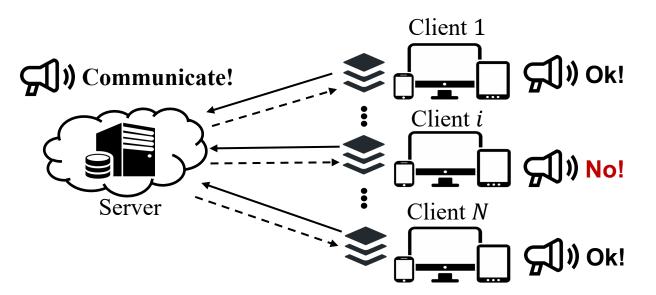
Focus: efficient communication protocol design that trades off communication cost and regret.

$$R_T = \sum_{t=1}^{NT} r_t$$
, where $r_t = \max_{x \in A_t} f(x) - f(x_t)$

Unveiling the Achilles' Heel: existing protocols essentially require/assume full client engagement whenever communication is triggered, however, what if clients are reluctant to share data and opt-out?

Problem Formulation

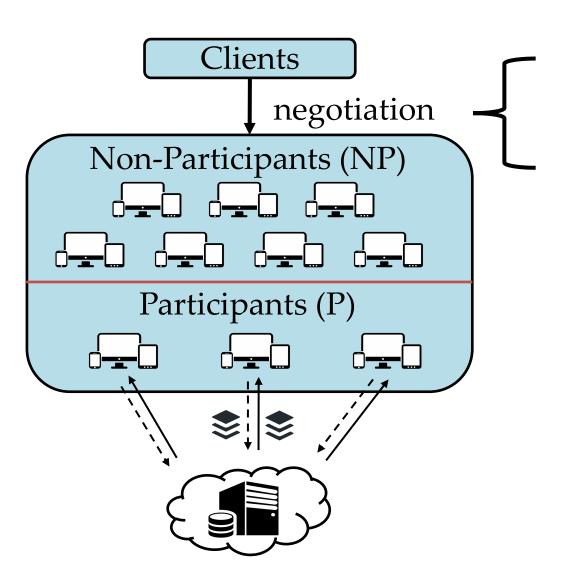
Incentivized Federated Bandits



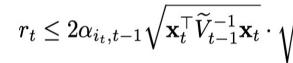
Incentivized Problem Setting: clients are self-interested, and will not share their data with the server unless the benefits outweigh any potential loss of sharing, e.g., privacy breaches. This is characterized by:

- Client decides whether to share data
- Server can motivate clients by providing incentives

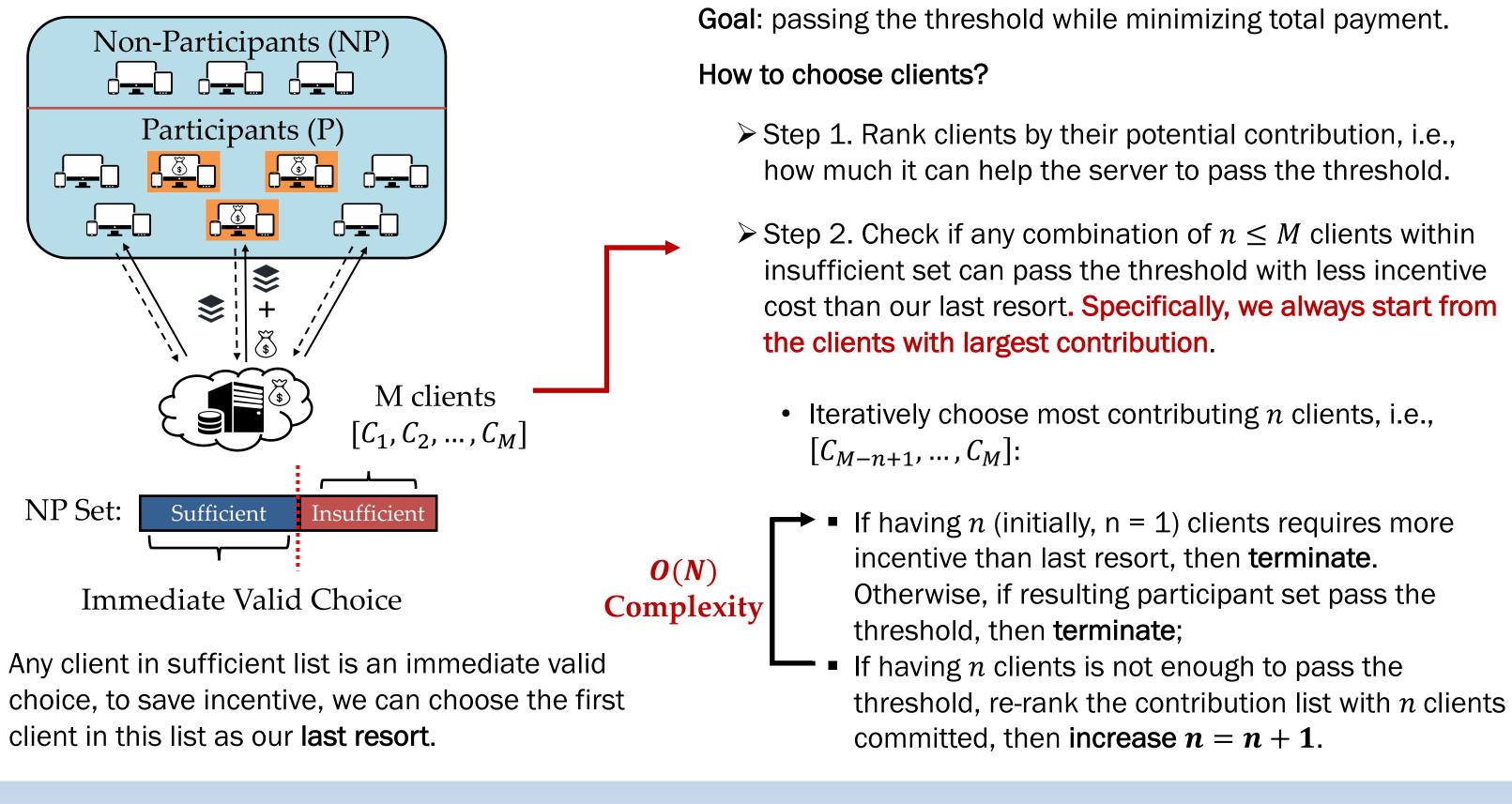
Research Question: how to design an incentivized communication protocol that balances multiple objectives, i.e., achieving nearly-optimal regret, with reasonable communication and incentive costs?



Regret Bound



We proved that, to achieve near-optimal regret, it is required that the shared data at each communication round is at least above a threshold compared to all available data in the system.



Incentivized Communication for Federated Bandits Zhepei Wei[†], Chuanhao Li[†], Haifeng Xu[‡], Hongning Wang[†]

[†]University of Virginia, [‡]University of Chicago

Payment-Free Design: Data as Incentive

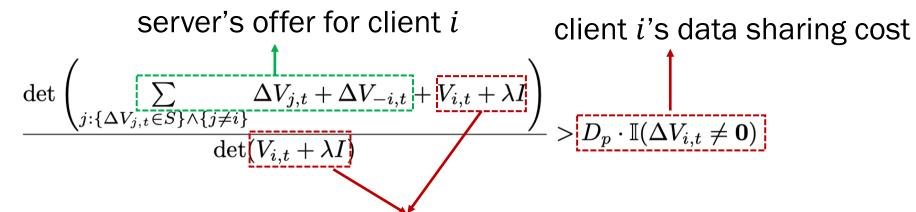
Server: if you share data, I will:

• Offer my reserved data and other participants' uploads

Client: I only care about myself, I will:

- Participate, if your offer exceeds my data sharing cost
- Not participate, otherwise

Data valuation



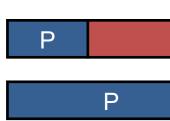
client *i*'s local data

$$\sqrt{\frac{\det(\widetilde{V}_{t-1})}{\det(V_{i_t,t-1})}} = O\left(\sqrt{d\log\frac{T}{\delta}}\right) \cdot \|\mathbf{x}_t\|_{\widetilde{V}_{t-1}^{-1}} \cdot \sqrt{\frac{\det(\widetilde{V}_{t-1})}{\det(V_{i_t,t-1})}}$$

However, as this payment-free data exchange cannot force participation, it can not guarantee regret.

Regret not Guaranteed :

Regret Guaranteed:



Payment-Efficient Design: Money as Additional Incentive



Theoretical & Empirical Results

We prove that, the proposed payment-efficient solution achieves **near-optimal regret** $R_T = O(d\sqrt{T} \log T)$, with communication cost $C_T = O(d^3 N^2 \log T)$ and incentive $\operatorname{cost} M_T = O\left(\max D_p \times P \times N - \sum_{i=1}^N P_i \times \left(\frac{\det \lambda I}{\det V_T}\right)^{1/P_i}\right)$ where P_i is the number of epochs client *i* get paid, *P* is the number of epochs.

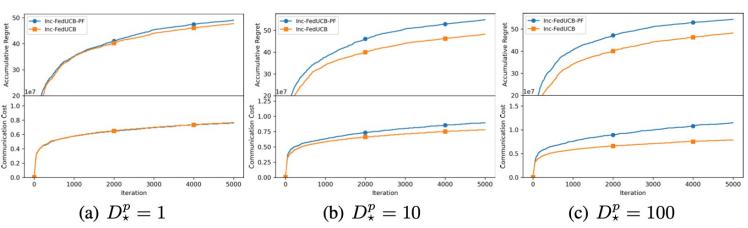


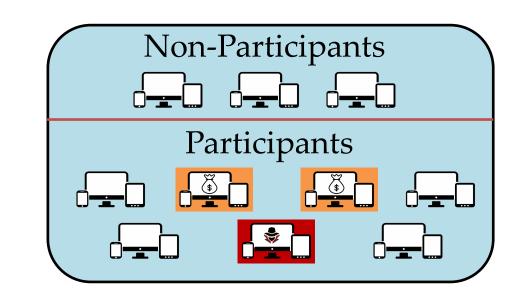
Figure 1: Comparison between payment-free vs. payment-efficient incentive designs.

d=25, K=25		DisLinUCB	Inc-FedUCB ($\beta = 1$)	INC-FEDUCB ($\beta = 0.7$)	INC-FEDUCB ($\beta = 0.3$)
$T = 5,000, N = 50, D_{\star}^{p} = 0$	Regret (Acc.)	48.46	48.46	48.46 ($\Delta=0\%$)	48.46 ($\Delta=0\%$)
	Commu. Cost	7,605,000	7,605,000	7,605,000 ($\Delta=0\%$)	7,605,000 ($\Delta=0\%$)
	Pay. Cost	١	0	$0~(\Delta=0\%)$	$0~(\Delta=0\%)$
$T = 5,000, N = 50, D_{\star}^{p} = 1$	Regret (Acc.)	١	48.46	47.70 ($\Delta - 1.6\%$)	$48.38~(\Delta - 0.2\%)$
	Commu. Cost	١	7,605,000	7,668,825 ($\Delta + 0.8\%$)	7,733,575 ($\Delta + 1.7\%$)
	Pay. Cost	١	75.12	$60.94~(\Delta - 18.9\%)$	$22.34~(\Delta - 70.3\%)$
$T = 5,000, N = 50, D_{\star}^{p} = 10$	Regret (Acc.)	١	48.46	$48.21~(\Delta-0.5\%)$	47.55 ($\Delta - 1.9\%$)
	Commu. Cost	١	7,605,000	7,779,425 ($\Delta + 2.3\%$)	8,599,950 ($\Delta + 13\%$)
	Pay. Cost	١	12,819.61	9,050.61 ($\Delta - 29.4\%$)	4,859.17 ($\Delta - 62.1\%$)
$T = 5,000, N = 50, D_{\star}^{p} = 100$	Regret (Acc.)	١	48.46	$48.22~(\Delta-0.5\%)$	48.44 ($\Delta - 0.1\%$)
	Commu. Cost	١	7,605,000	7,842,775 ($\Delta + 3.1\%$)	8,718,425 ($\Delta + 14.6\%$)
	Pay. Cost	١	190,882.45	133,426.01 (<u>Δ</u> - <u>30.1</u> %)	88,893.78 (Δ – 53.4%)

Table 1: Study on Hyper-Parameter of INC-FEDUCB and Environment

Future Work

New Challenge: some adversarial clients may misreport their data sharing costs, and take advantage of the server to increase their utility.



Research Question: how can we incentivize clients in a way that encourages them to truthfully report their costs in their best interest?

Acknowledgement

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