

STACKELBERG GAMES

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Introduction

Pure Strategy Stackelberg Equilibria

Mixed Strategy Stackelberg Equilibria

Federated Learning

Stackelberg Game Formulation in Federated Learning

Results and Analysis

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INTRODUCTION

Two player finite game

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P1 is powerful enough to impose his strategy on the other player

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Government setting up policies for spectrum auction

Government setting up policies for spectrum auction ←— Leader

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Participating companies coming up with strategies based on the government's policy

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Antivirus company releasing update

Antivirus company releasing update ← Leader

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Malicious agents' strategy to exploit the loopholes

Antivirus company releasing update ←— Leader

Malicious agents' strategy to exploit the loopholes ←— Follower

PURE STRATEGY STACKELBERG EQUILIBRIA

Two player finite game

$$A = \begin{bmatrix} 0 & 2 & 1.5 \\ 1 & 1 & 3 \\ -1 & 2 & 2 \end{bmatrix}, B = \begin{bmatrix} -1 & 1 & -\frac{2}{3} \\ 2 & 0 & 1 \\ 0 & 1 & -\frac{1}{2} \end{bmatrix}$$

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What is the NE?

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What is the NE?

$\implies j^* = 2$ and $k^* = 2$

\implies Associated cost = $(1, 0)$

Two player finite game

Two player finite game

P1 is the leader and P2 is the follower

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What is the safest strategy for P1?

$$\Rightarrow j^* = 1$$

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What is the best strategy for P2, knowing $j^* = 1$?

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Note: The cost is lesser than the NE cost (for both the players).

Is it always the case?

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→ No!

Same cost matrices but P2 as leader and P1 as follower

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\implies The cost is lesser than the NE cost for only P2 (from 0 to $-\frac{2}{3}$)

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Note:

\implies The cost is lesser than the NE cost for only P2 (from 0 to $-\frac{2}{3}$)

\implies Cost increases for P1 (from 1 to 1.5)

Does Stackelberg game setup always reduce the cost for either of the players, when compared with NE?

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⇒ NE at (2, 3)

⇒ Associated cost (-1, -1)

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Choose P1 as leader

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Choose P1 as leader

$$\Rightarrow j^* = 1$$

$$\Rightarrow k^* = 1 \text{ or } 2$$

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Choose P1 as leader

$$\Rightarrow j^* = 1$$

$$\Rightarrow k^* = 1 \text{ or } 2$$

$$\Rightarrow \text{Associated cost} = (0, 0) \text{ or } (1, 0)$$

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Choose P1 as leader

$$\Rightarrow j^* = 1$$

$$\Rightarrow k^* = 1 \text{ or } 2$$

\Rightarrow Associated cost = (0,0) or (1,0)

\Rightarrow Cost increases for both P1 and P2

Notations:

$\mathcal{G}(I, \Omega_i, J_i), I = 1, 2$

P1: $u_1 \in \Omega_1, |\Omega_1| = m \leftarrow$ Set of indices $M1 = \{1, \dots, j, \dots, m\}$

P2: $u_2 \in \Omega_2, |\Omega_2| = n \leftarrow$ Set of indices $M2 = \{1, \dots, k, \dots, n\}$

P1: Cost function $J_1 : \Omega_1 \times \Omega_2 \rightarrow \mathbb{R}$

P2: Cost function $J_2 : \Omega_1 \times \Omega_2 \rightarrow \mathbb{R}$

P1 is leader and P2 is the follower

Definition:

In a two-player finite game, with P1 being the leader choosing $u_1 \in \Omega_1$ as his strategy, optimal response of P2 or $BR_2(u_1) \subset \Omega_2$ is defined as,

$$BR_2(u_1) = \{u_2^* \in \Omega_2 : J_2(u_1, u_2^*) \leq J_2(u_1, u_2), \forall u_2 \in \Omega_2\}$$

STACKELBERG GAME FORMULATION (IN PURE STRATEGY)

What is the Stackelberg cost for P1?

STACKELBERG GAME FORMULATION (IN PURE STRATEGY)

Definition:

In a two-player finite game, with P1 being the leader, $u_1 \in \Omega_1$ is the Stackelberg equilibrium strategy for P1,

$$J_1^* = \min_{u_1 \in \Omega_1} \max_{u_2 \in BR_2(u_1^*)} J_1(u_1, u_2)$$

Similar formulation can be obtained choosing P2 as leader

Definition:

P1 being the leader with optimal strategy $u_1^* \in \Omega_1$ and P2 with the optimal strategy $u_2^* \in BR_2(u_1^*)$ Stackelburg solution of the game is defined by $u^* = (u_1^*, u_2^*)$.

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\implies The associated cost for P1: $J_1^* = J_1(u_1^*, u_2^*)$

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Note:

\implies The associated cost for P1: $J_1^* = J_1(u_1^*, u_2^*)$

\implies The associated cost for P2: $J_2^* = J_2(u_1^*, u_2^*)$

\implies Cost for P1 in NE: J_1^{NE} .

Theorem:

If $BR_2(u_1)$ is a singleton for $u_1 \in \Omega_1$, then,

$$J_1^* \leq J_1^{NE}$$

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Proof. Can be proven by contradiction.

MIXED STRATEGY STACKELBERG EQUILIBRIA

Recall from the pure strategy case

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$\implies u_1 \in \Omega_1$ and $u_2 \in \Omega_2$ both are finite set. Also $BR_2(u_1) \in \Omega_2$ is also a finite set for all $u_1 \in \Omega_1$

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Why do we need mixed strategy?

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\implies P1 declares his strategy beforehand

Why do we need mixed strategy?

\implies Turns out, P1 can reduce his cost by choosing mixed strategy over pure strategy

$\implies \mathcal{G}(I, \Omega_i, J_i), I = 1, 2$

\implies Set of actions for P1: $\Omega_1, |\Omega_1| = m \leftarrow$ Set of indices

$M1 = \{1, \dots, j, \dots, m\}$.

\implies Set of actions for P2: $\Omega_2, |\Omega_2| = n \leftarrow$ Set of indices

$M2 = \{1, \dots, k, \dots, n\}$.

\implies Probability of P1 selecting j^{th} action: $x_j, \sum_{j=1}^m x_j = 1$ and $0 \leq x_j \leq 1$.

\implies Probability of P2 selecting k^{th} action: $y_k, \sum_{k=1}^n y_k = 1$ and $0 \leq y_k \leq 1$.

$\implies \mathbf{x} = [x_1, \dots, x_j, \dots, x_m]^T$ and $\mathbf{y} = [y_1, \dots, y_k, \dots, y_n]^T$

\implies Mixed strategy set for P1: $\Delta_1 = \{\mathbf{x} \in \mathbb{R}^m \mid 0 \leq x_j \leq 1 \forall j; \sum_{j=1}^m x_j = 1\}$.

\implies Mixed strategy set for P2: $\Delta_2 = \{\mathbf{Y} \in \mathbb{R}^n \mid 0 \leq y_k \leq 1, \forall k; \sum_{k=1}^n y_k = 1\}$.

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} \frac{1}{2} & 1 \\ 1 & \frac{1}{2} \end{bmatrix}$$

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⇒ Associated cost in NE: $(1, \frac{1}{2})$

⇒ P1 mixes his strategy $\mathbf{x}^* = [\frac{1}{2}, \frac{1}{2}]^T$.

Mixed strategy for P2 would be:

$$\mathbf{y}^* = \arg \min_{y \in \Delta_2} \mathbf{x}^* B \mathbf{y} \quad (1)$$

$$= \arg \min_{y \in \Delta_2} \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} \frac{1}{2} & 1 \\ 1 & \frac{1}{2} \end{bmatrix} \mathbf{y} \quad (2)$$

$$= \arg \min_{y \in \Delta_2} \begin{bmatrix} \frac{3}{4} & \frac{3}{4} \end{bmatrix} \mathbf{y} \quad (3)$$

$$(4)$$

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} \frac{1}{2} & 1 \\ 1 & \frac{1}{2} \end{bmatrix}$$

⇒ Associated cost in NE: $(1, \frac{1}{2})$

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⇒ Expected cost in mixed strategy: $(\frac{1}{2}, \frac{3}{4})$

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⇒ Mixed strategy led to reduction in P1's cost

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Does a mixed strategy Stackelberg equilibria always exist?

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Does a mixed strategy Stackelberg equilibria always exist?

Not really!

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⇒ There is no Stackelberg equilibrium in mixed strategies.

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⇒ There is no Stackelberg equilibrium in mixed strategies.

⇒ There exists sub-optimal mixed strategy.

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⇒ There is no Stackelberg equilibrium in mixed strategies.

⇒ There exists sub-optimal mixed strategy.

If Stackelberg mixed strategy exists, how is it related to NE?

Theorem:

For a two player finite game, if the Stackelberg mixed strategy equilibria exists, then the following holds,

$$J_1' \leq J_1^{NE}$$

Takeaways:

⇒ In a two player finite game, mixed strategy NE would always exist.
Whereas, a mixed strategy Stackelberg equilibrium might not exist.

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⇒ In a two player finite game, mixed strategy NE would always exist.

Whereas, a mixed strategy Stackelberg equilibrium might not exist.

⇒ If the mixed strategy Stackelberg equilibria exist, the player would incur lower cost than that of the NE.

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⇒ Federated learning!

FEDERATED LEARNING

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Goal

K number of users wish to train a state-of-the-art machine learning model, collectively, without sharing their respective data $\mathcal{D}_i, \forall i \in 1, \dots, K$; to other users.

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3. In order to train a machine learning model, with parameters w , on the labeled data points (\mathbf{x}, \mathbf{y}) for each k , we consider a local objective function of $f^k(w) = \frac{1}{n^{(k)}} \sum_{i \in \mathbf{S}} l(x_i, y_i; w)$.

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4. In a federated setting, we can write the objective function $f^f(w)$ in the following form,

$$\min_w f^f(w) = \sum_{k=1}^K p_k f^k(w) = \mathbb{E}_k[f^k(w)]$$

where $p_k = \frac{n^{(k)}}{n}$, $p_k \geq 0$ & $\sum_k p_k = 1$

How to motivate workers?

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Stackelberg game formulation to address the challenges?

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Stackelberg game formulation to address the challenges?

Work by Sarikaya and Erçetin indicates that ¹

¹Yunus Sarikaya and Özgür Erçetin, "Motivating Workers in Federated Learning: A Stackelberg Game Perspective", *Arxiv*, Aug. 2019. [Online] <https://arxiv.org/abs/1908.03092>

STACKELBERG GAME FORMULATION IN FEDERATED LEARNING

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- ⇒ If the server agrees to pay q_k to k -th worker for per unit of CPU power, worker k would get $q_k P_k$ from the server to perform the t -th update.

⇒ Server's cost function J' , it can be defined as follows,

$$J'(q_k, P_k) = \alpha \mathbb{E} \left[\max_k T_{k,t} \right] + \sum_{k=1}^K q_k P_k$$

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⇒ Cost function of the worker, J'' , can be defined by,

$$J''_k(P_k, q_k) = q_k P_k - \kappa c_k (P_k)^2$$

where κ is a chip architecture dependent constant

⇒ The game formulation for the worker can be as follows:

$$\begin{aligned} \max_{P_k} J_k''(P_k, q_k) &= q_k P_k - \kappa c_k (P_k)^2 \\ \text{s.t. } P_k &\leq P_{\max} \end{aligned}$$

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⇒ Game formulation for the server would be,

$$\begin{aligned} \min_q J' &= \alpha \mathbb{E}[\max_k T_{k,t}] + \sum_{k=1}^K q_k P_k \\ \text{s.t. } \sum_{k=1}^K q_k P_k &\leq B \end{aligned}$$

where B is the available budget to the server to pay the workers.

⇒ Solving for the worker's game,

$$P_k^*(q_k) = \begin{cases} \frac{q_k}{2\kappa c_k} & \text{if } \frac{q_k}{2\kappa c_k} \leq P_{\max} \\ P_{\max} & \text{if } \frac{q_k}{2\kappa c_k} > P_{\max} \end{cases}$$

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⇒ Optimal solution for the server $q_k^* = \sqrt{\frac{2B\kappa c}{K}}$

RESULTS AND ANALYSIS

SIMULATION RESULTS

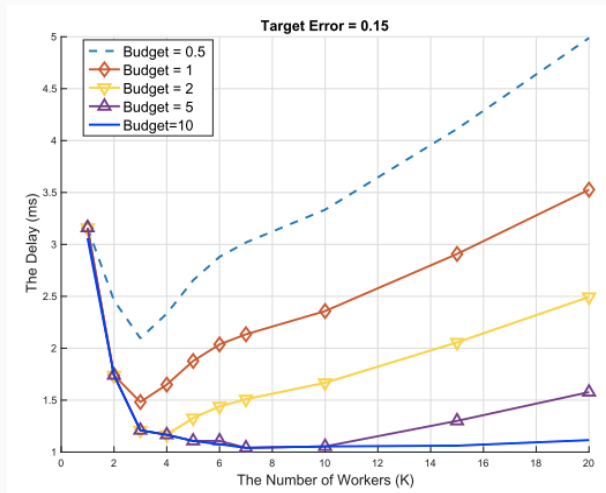


Figure: Analysis of delay with increase in K

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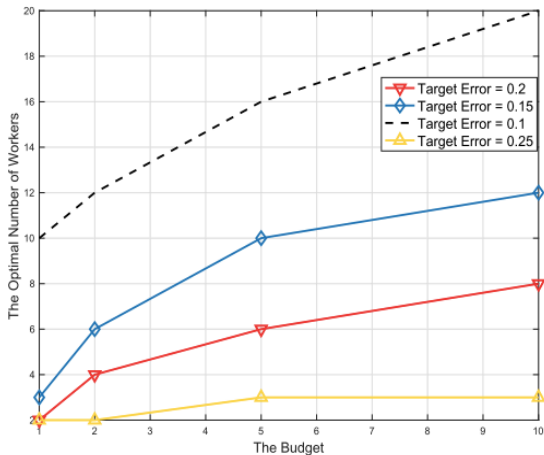


Figure: Analysis of availability of budget and optimality of number of workers

CONCLUSIONS & FUTURE WORKS

⇒ Laying out the motivations behind studying the Stackelberg game, with relevant examples

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- ⇒ Defining the problem of federated learning and its connection with the Stackelberg game formulation
- ⇒ Understanding the cost function formulation and obtaining the Stackelberg equilibria solution for federated learning.

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⇒ Authors considered the case of all honest workers ← Can a number of dishonest workers manipulate the server to allocate more resource?

BACKUP SLIDES

CENTRALIZED LEARNING

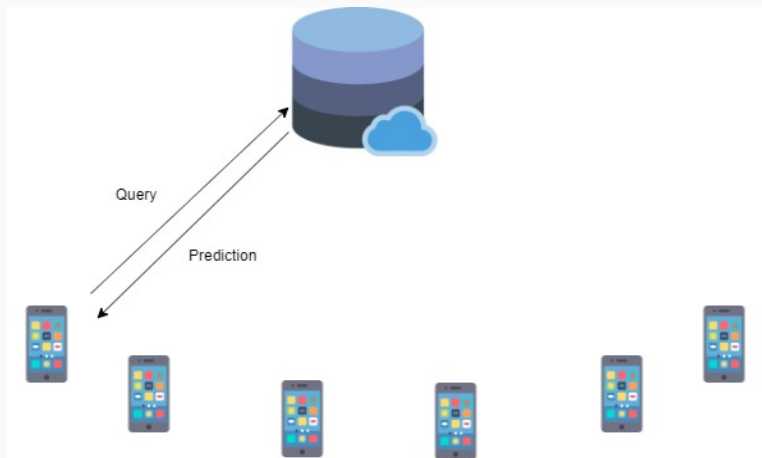


Figure: Centralized learning

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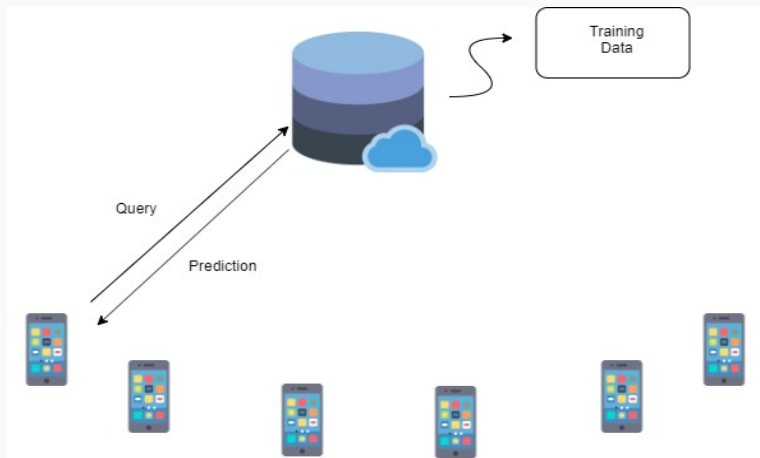


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FEDERATED LEARNING

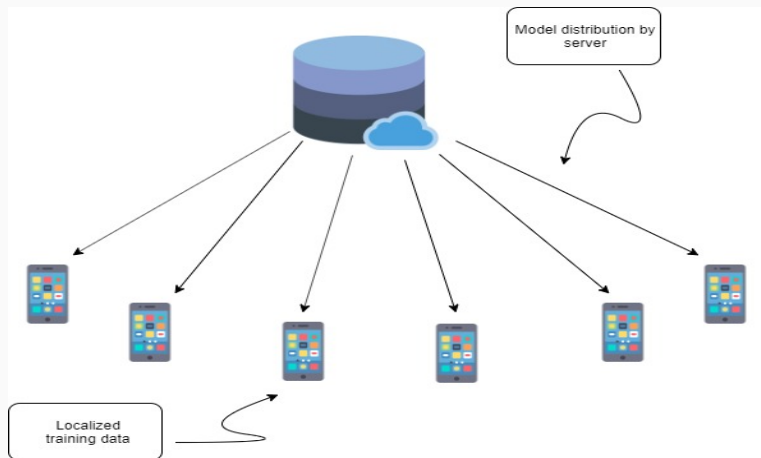


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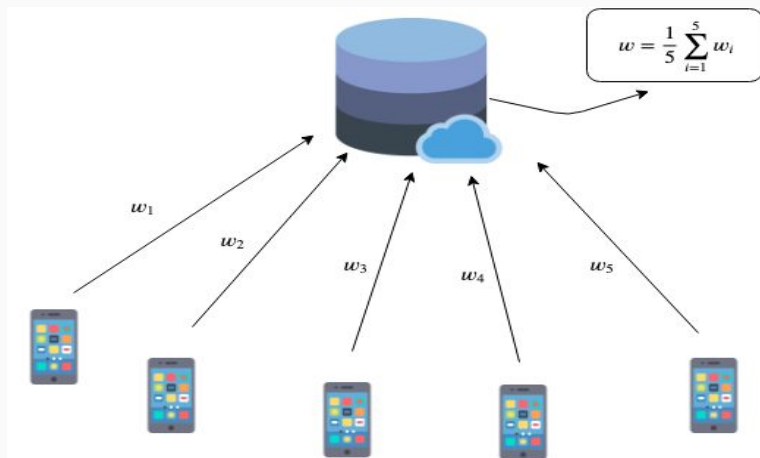


Figure: Federated learning

Until Convergence:

Server:

1. Select K number of users randomly.
2. Send w_t , i.e. parameter update at t^{th} iteration, to all K users.

User:

1. Download parameter update w_t from the server.
 2. Run SGD locally, for E epochs, and obtain w_t^k .
 3. Upload $w_t - w_t^k$ to the server.
3. $w_{t+1} = w_t +$ weighted average of the parameter updates by K users.

²McMahan et al, 'Communication-efficient Learning of Deep Networks from Decentralized Data', AISTATS, 2017.