About me

- Ph.D. candidate at NUS and funded by A*STAR,
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Agenda:

1. **Motivations and overview of Collaborative Machine Learning (CML)**
2. **Our NeuIPS'21 paper: "Gradient-Driven Rewards to Guarantee Fairness in Collaborative Machine Learning"**
3. **Brief follow-up on our most recent works addressing some open issues.**
4. **Q & A**

Importance of data in ML

- “Supervised learning, while successful in a wide variety of tasks, typically requires a **large** amount of human-labeled data …” - Yoshua Bengio, Geoffrey Hinton, and Yann LeCun [1].
- “In many industries where giant data sets simply don’t exist, I think the focus has to shift from big data to **good data** …” - Andrew Ng [2].

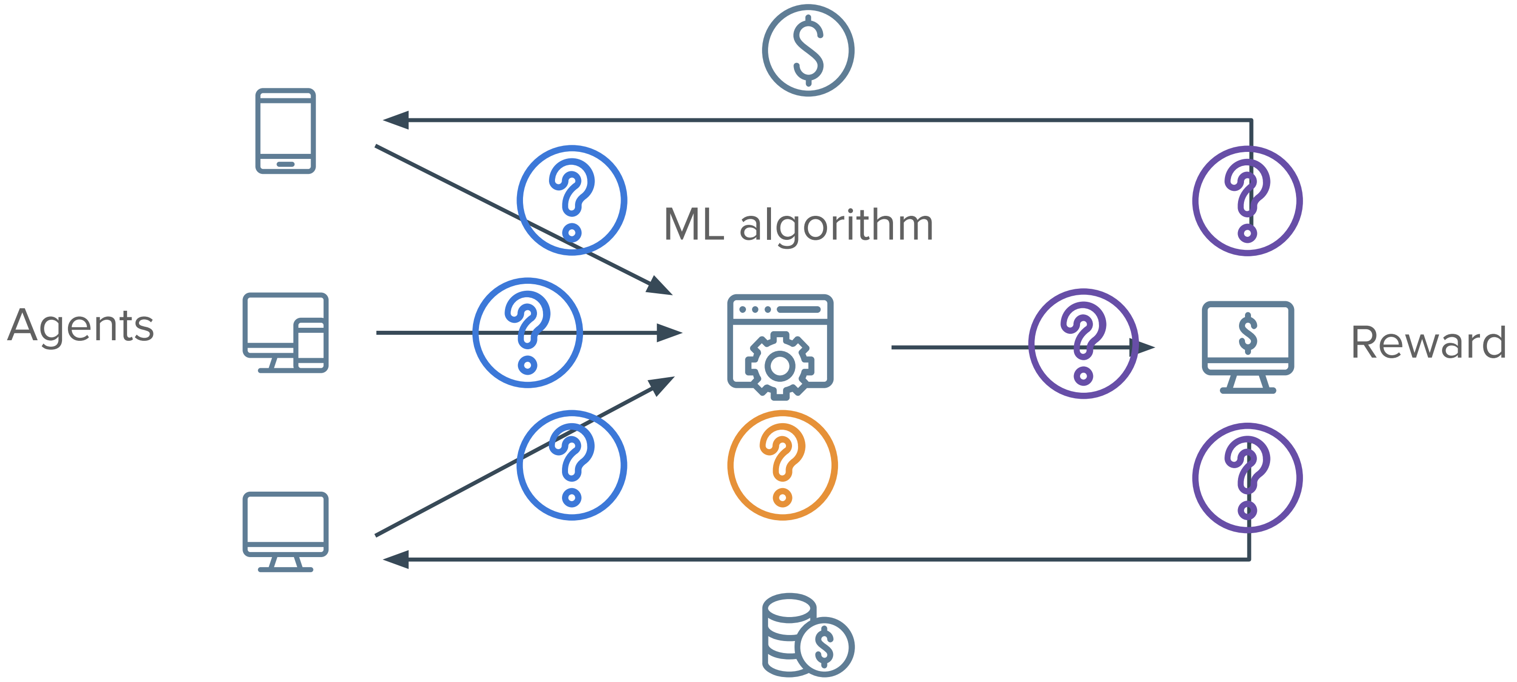
For ML to be effective, a **large** amount of **good/high-quality** data are needed.

[1] Deep Learning for AI, Turing Lecture, Communications of the ACM, July 2021, Vol. 64 No. 7, Pages 58-65.
[2] https://spectrum.ieee.org/andrew-ng-data-centric-ai, accessed 2022 May 30th.

Motivations for CML

- **Quantity** - Distributing the burden of data collection (in cross-silo FL) or effectively utilizing naturally distributed data (e.g., in cross-device FL).
- **Quality** - Data valuation to identify good/high-quality data in the specific ML use-cases.
    - The same data are not equally valuable for different ML algorithms; the same data are not equally valuable if others have access.
    - Another application is for pricing in AI marketplace.

Collaborative Machine Learning (CML)



Gradient-Driven Rewards to Guarantee Fairness in Collaborative Machine Learning

Xinyi Xu[1,5], Lingjuan Lyu[2], Xingjun Ma[3], Chenglin Miao[4], Chuan Sheng Foo[5], Bryan Kian Hsiang Low[1]

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Federated learning (FL)

Suppose N self-interested and honest agents, each with a local dataset $\mathcal{D}_i$. The federated objective is:

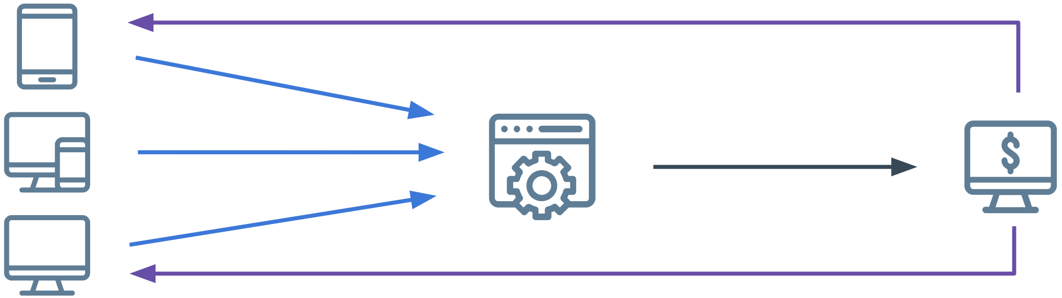
$$\boldsymbol{w}^* = \arg\min_w \sum_i p_i \mathbf{F}(\boldsymbol{w}; \mathcal{D}_i)$$

In iteration *t*:

For *Agent i*: $\Delta\boldsymbol{w}_{i,t} \leftarrow -\eta \nabla \mathbf{F}(\boldsymbol{w}_{i,t}; \mathcal{D}_i)$

For *Server*: $\boldsymbol{u}_{\mathcal{N},t} \leftarrow \sum_i p_i \Gamma \frac{\Delta\boldsymbol{w}_{i,t}}{\|\Delta\boldsymbol{w}_{i,t}\|}$

$$\boldsymbol{w}_{i,t+1} \leftarrow \boldsymbol{w}_{i,t} + \boldsymbol{u}_{\mathcal{N},t}$$



Should every agent be rewarded equally? otherwise how?

p_i is an importance coefficient, Γ is a normalizing constant and $\mathcal{N} := \{i; 1 \leq i \leq N\}$ denotes all the agents.

Fair training-time rewards

Instead of rewarding all the agents **equally**, reward them **fairly**: Agents that upload more valuable gradients are rewarded better.

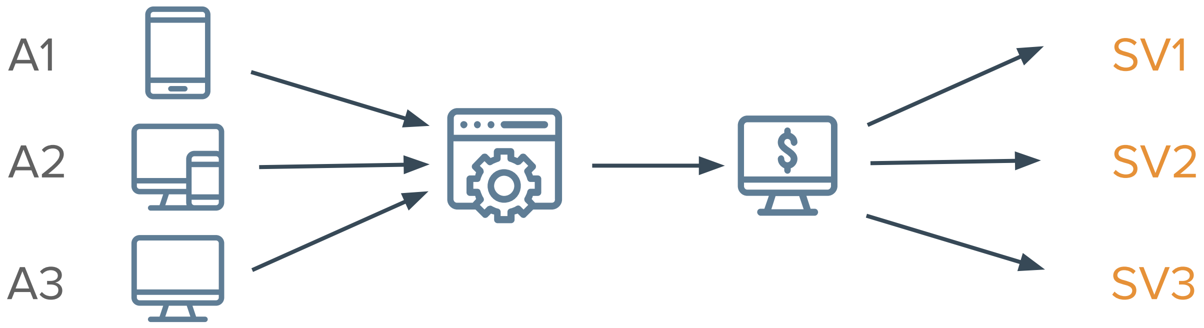
- Incentivize the agents to collect more data of higher quality.

1. How to determine the values of (the gradients of) the agents fairly?
2. How to guarantee the rewards are fair?

Fair training-time rewards

1. How to determine the values of (the gradients of) the agents fairly?

   The **Shapley value** (SV) with several intuitive fairness properties.



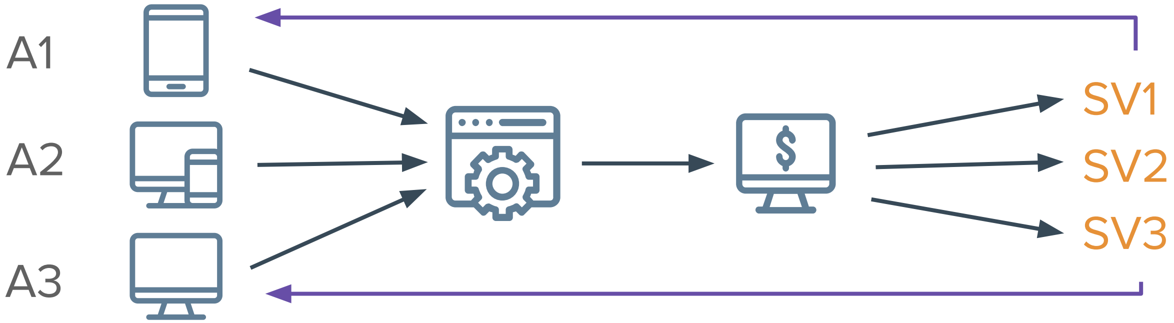
null player: if an agent uploads non-valuable gradients, the corresponding SV is zero.

symmetry: if two agents upload identical (equally valuable) gradients, their corresponding SVs are equal.

Fair training-time rewards

2. How to guarantee the rewards are fair?

A higher **SV** leads to a better **downloaded gradient**.



For an agent *i*:

- contributing more (while others remain the same) leads to a better reward;
- contributing more than agent *j* leads to a better reward than agent *j*.

Fair **training-time** rewards

2. How to guarantee the rewards are fair?

In each iteration, the agents are **rewarded with carefully managed gradients**.

- inherent rewards: no need for additional external resources;
- the agents do not need to wait till the end [1,2];
- *local-to-global*: **fairness** in each iteration → **fairness** overall (Theorem 2).

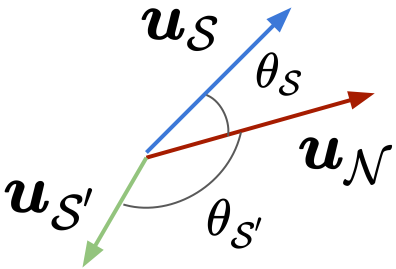
[1] Profit Allocation for Federated Learning. Tianshu Song, Yongxin Tong, Shuyue Wei, IEEE Big Data, 2019.
[2] A Principled Approach to Data Valuation for Federated Learning. Tianhao Wang, Johannes Rausch, Ce Zhang, Ruoxi Jia, Dawn Song, 2020, LNCS.

Cosine gradient Shapley value (CGSV)

Definition 1 (Cosine gradient Shapley value (CGSV)). Let $\Pi_{\mathcal{N}}$ be a set of all possible permutations of $\mathcal{N}$ and $\mathcal{S}_{\pi,i}$ be the coalition of agents preceding agent i in permutation $\pi \in \Pi_{\mathcal{N}}$. The CGSV of agent $i \in \mathcal{N}$ is defined as

$$\phi_i := (1/N!) \sum_{\pi \in \Pi_{\mathcal{N}}} \left[\nu(\mathcal{S}_{\pi,i} \cup \{i\}) - \nu(\mathcal{S}_{\pi,i})\right]. \quad (2)$$

The *gradient valuation function:* $\nu(\mathcal{S}) = \cos(\boldsymbol{u}_{\mathcal{S}}, \boldsymbol{u}_{\mathcal{N}})$ where $\boldsymbol{u}_i \leftarrow \Gamma \frac{\Delta \boldsymbol{w}_i}{\|\Delta \boldsymbol{w}_i\|}$, $\boldsymbol{u}_{\mathcal{S}} \leftarrow \sum_{i \in \mathcal{S}} p_i \boldsymbol{u}_i$



$$\nu(\mathcal{S}) = \cos(\boldsymbol{u}_{\mathcal{S}}, \boldsymbol{u}_{\mathcal{N}}) = \cos(\theta_{\mathcal{S}})$$

$$\nu(\mathcal{S}) > \nu(\mathcal{S}')$$

$$\nu(\mathcal{S}') = \cos(\boldsymbol{u}_{\mathcal{S}'}, \boldsymbol{u}_{\mathcal{N}}) = \cos(\theta_{\mathcal{S}'})$$

- The CGSV ϕ_i of an uploaded gradient $\boldsymbol{u}_i$ (i.e., contribution from agent *i*) is evaluated via the vector alignment between $\boldsymbol{u}_i$ and $\boldsymbol{u}_{\mathcal{N}}$, via the cosine similarity [1].

[1] A Reputation Mechanism Is All You Need: Collaborative Fairness and Adversarial Robustness in Federated Learning. Xinyi Xu, Lingjuan Lyu. 2021 FL-ICML workshop (Oral).

Efficiently Approximating CGSV

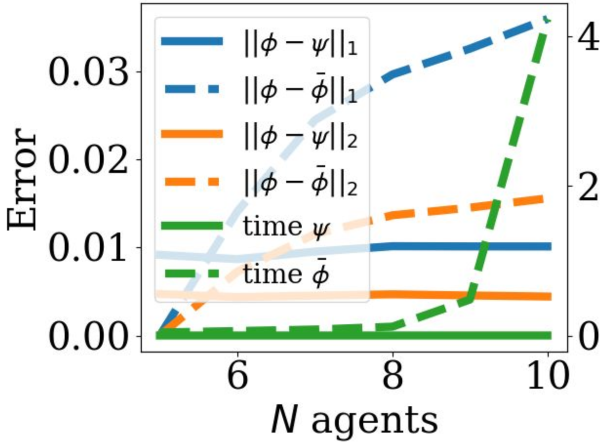
- Computing the exact CGSV incurs $\mathcal{O}(2^N D)$ which is practically infeasible for larger *N*.
- We provide an efficient approximation (with a bounded error) as:

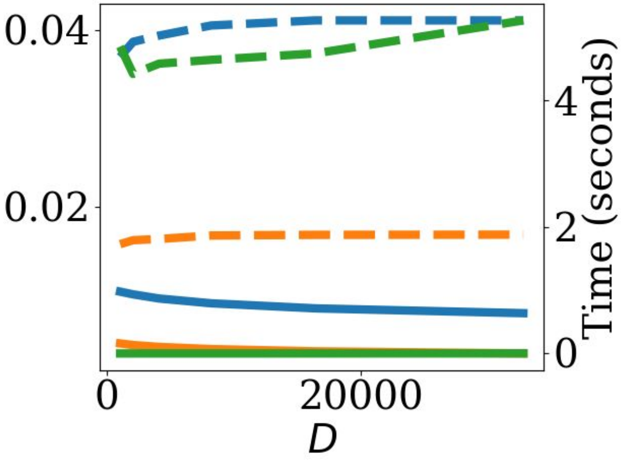
$$\phi_i \approx \psi_i = \cos(\boldsymbol{u}_i, \boldsymbol{u}_{\mathcal{N}})$$

Theorem 1 (Approximation Error). *Let* $I \in \mathbb{R}^+$. *Suppose that* $\|\boldsymbol{u}_i\| = \Gamma$ *and* $|\langle \boldsymbol{u}_i, \boldsymbol{u}_{\mathcal{N}} \rangle| \geq 1/I$ *for all* $i \in \mathcal{N}$. *Then,* $\phi_i - L_i \psi_i \leq I\Gamma^2$ *where the multiplicative factor* L_i *can be normalized away.*

- Intuition: exploit linearity of CGSV and linearity of cosine similarity to “branch and bound”.
- It reduces the complexity to $\mathcal{O}(ND)$ and we empirically demonstrate its effectiveness against a Monte Carlo sampling-based $(\epsilon, \delta)-$approximation.

Efficiently Approximating CGSV





- We compare ℓ_1, ℓ_2 errors with the exact value and runtime against *N* and *D*.
- Solid lines denote our approximation and lower is better.
- Our approximation performs better for all 3 metrics and the performance gap widens as *N* increases.

Server-Side Training-Time Gradient Reward Mechanism

- **Gradient aggregation** (by *Server*)
  - Update the contribution:

$$r_{i,t} \leftarrow \alpha\, r_{i,t-1} + (1-\alpha)\, \psi_{i,t}\ ,\ r_{i,t} \leftarrow \frac{r_{i,t}}{\sum_{i' \in \mathcal{N}} r_{i',t}}$$

    - The cumulative update over iterations helps reduce fluctuations and provide a smoother estimate of the contributions of the agents.

  - Compute the aggregate gradient:

$$\boldsymbol{u}_{\mathcal{N},t} \leftarrow \sum_i r_{i,t} \boldsymbol{u}_{i,t}$$

    - $r_{i,t}$ is then used as the importance coefficient to aggregate the gradient.

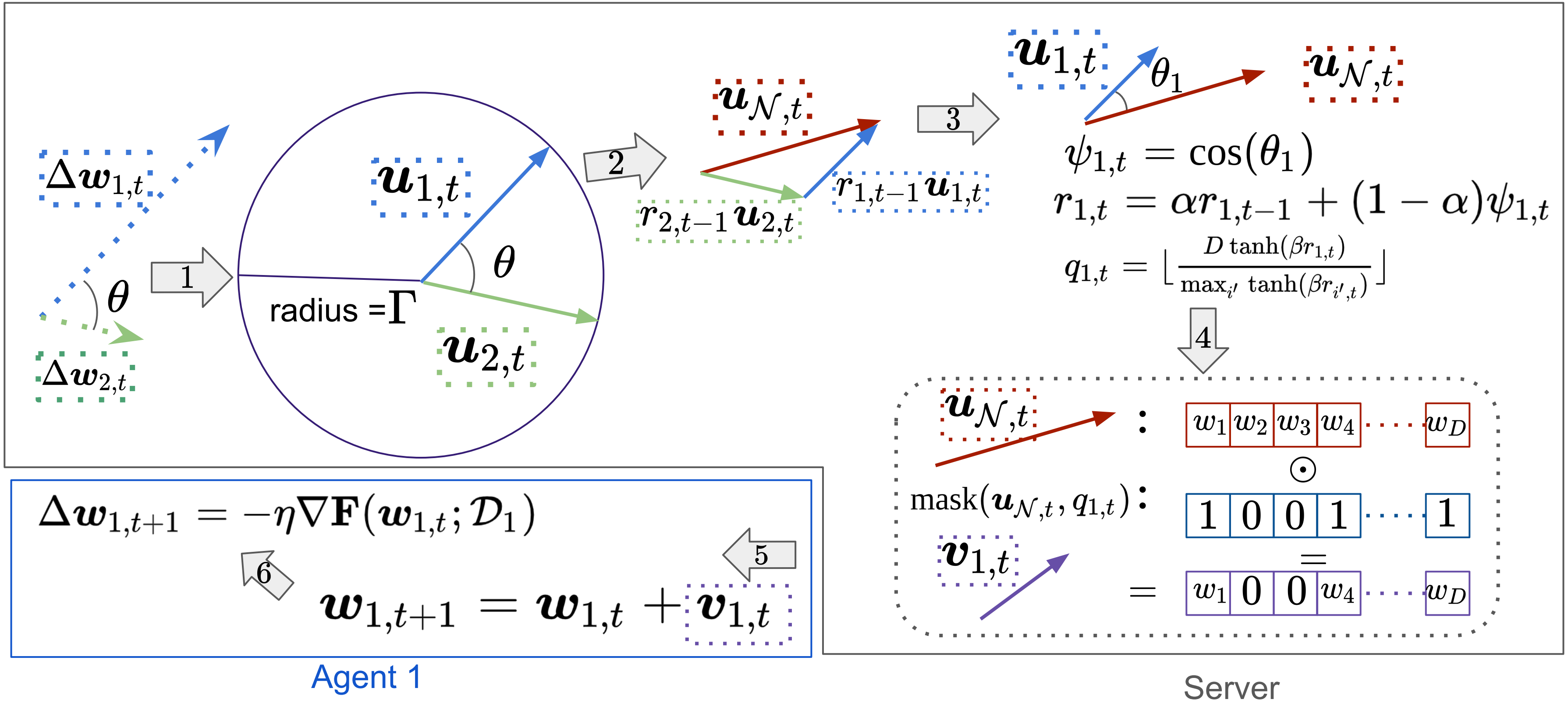
Server-Side Training-Time Gradient Reward Mechanism

- **Gradient download** (for *Agent i*)
  - Calculate the fair gradient reward s.t., "A higher **SV** leads to a better **downloaded gradient**."

$$\boldsymbol{v}_{i,t} \leftarrow \text{mask}(\boldsymbol{u}_{\mathcal{N},t}, q_{i,t}) \qquad q_{i,t} \leftarrow \left\lfloor \frac{D \tanh(\beta r_{i,t})}{\max_{i'} \tanh(\beta r_{i',t})} \right\rfloor \quad \in [0, 1]$$

    - *sparsification:* $\text{mask}(\boldsymbol{u}, q)$ retains the largest $\max(0, q)$ components in magnitude of $\boldsymbol{u}$ and zeros out all the rest. Lower sparsification (higher $q_{i,t}$) ⇔ better **downloaded gradient**.
    - $q_{i,t}$ is max-normalized cumulative **SV**: higher **SV** ⇔ higher $r_{i,t}$ ⇔ higher $q_{i,t}$.
    - *altruism degree* β **quantifies** how much an agent with *lower* contributions benefit
      larger β ⇔ more altruistic/equitable while smaller β ⇔ stricter fairness.
  - Update local model: $\boldsymbol{w}_{i,t} \leftarrow \boldsymbol{w}_{i,t-1} + \boldsymbol{v}_{i,t}$

Putting it all together



Global Fairness Guarantee

Theorem 2 (Fairness in Model Performance). *Define* $\delta_{i,t} := \|\boldsymbol{w}_{\mathcal{N},t} - \boldsymbol{w}_{i,t}\|$ *and* $\boldsymbol{w}_{\mathcal{N},t}$ *is near a stationary point of* $\mathbf{F}()$ *and some regularity conditions on the objective function* $\mathbf{F}(\cdot)$*. For any* $t \in \mathbb{Z}^+$ *and* $\forall i, i' \in \mathcal{N}$*, if* $r_{i,t} \geq r_{i',t}$ *and* $\delta_{i',t-1} - \delta_{i,t-1} \geq 2\|\boldsymbol{v}_{i,t}\|$*, then* $\mathbf{F}(\boldsymbol{w}_{i,t}) \leq \mathbf{F}(\boldsymbol{w}_{i',t})$.

- Local fairness to global fairness:
    - An agent that uploads better gradients can download better gradients (locally fair), and as a result, this agent receives a better-performing model (globally fair).
- Intuition:
    - all agents start with the same model: $\boldsymbol{w}_0$
    - agents with higher $r_{i,t}$ have less deviation from the trajectory: $\{\boldsymbol{w}_0 + \sum_{l=1}^{t} \boldsymbol{u}_{\mathcal{N},l}\}_t$

Experimental setup & baselines

- Datasets
  - MNIST, CIFAR-10, Movie Reviews, Stanford Sentiment Treebank
- Comparison baselines
  - FedAvg [1], and its variants
  - q-FFL [2], CFFL [3]
  - Shapley value-based: Extended contribution index (ECI) [4]
  - Euclidean distance variant instead of cosine similarity

- Data partitions
  - uniform (UNI)
  - powerlaw (POW)
    - Individual datasets of different **sizes**
  - classimbalance (CLA)
    - Individual datasets with different **available classes**

      e.g. MNIST, for N=5, the agents have {1,3,5,7,10} classes respectively

[1] Communication-Efficient Learning of Deep Networks from Decentralized Data. H. Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, Blaise Agüera y Arcas, 2017, AISTATS.
[2] Fair Resource Allocation in Federated Learning. Tian Li, Maziar Sanjabi, Ahmad Beirami, Virginia Smith. 2020, ICLR.
[3] Collaborative fairness in federated learning. Lingjuan Lyu, Xinyi Xu, Qian Wang. 2020, LNCS.
[4] Profit Allocation for Federated Learning. Tianshu Song, Yongxin Tong, Shuyue Wei, IEEE Big Data, 2019.

Fairness evaluation metric

Pearson correlation coefficient between **standalone performance** & **final local model performance**.

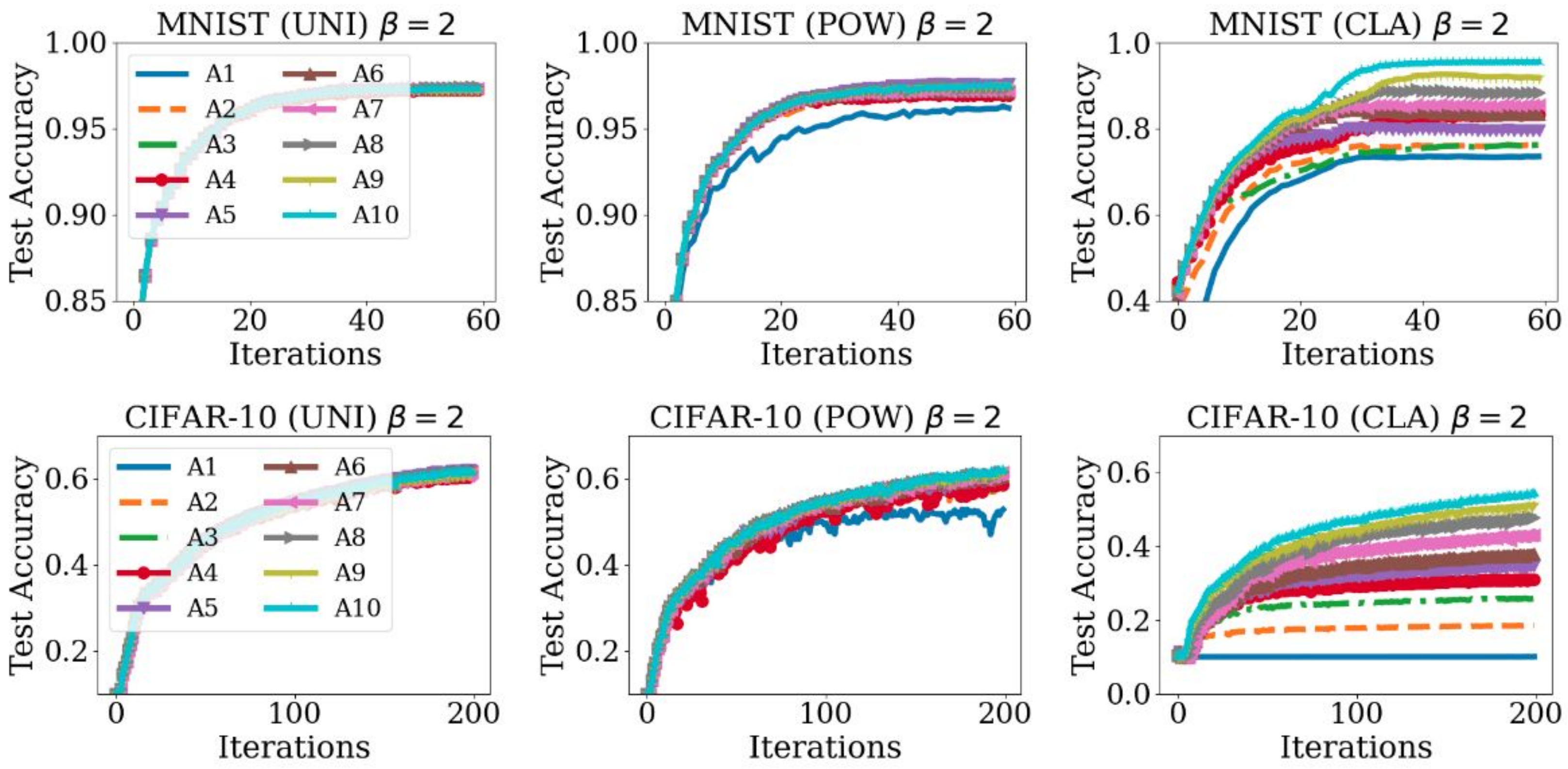
- Standalone performance provides an estimate of the quality of the local dataset and thus the quality of the contribution (via uploaded gradients) by the agents.
- Final local model performance represents the rewards the agents receive at the end.

*A correlation close to 1 indicates the **rewards** are commensurate with the **contributions** (i.e., fair), and validates Theorem 2.*

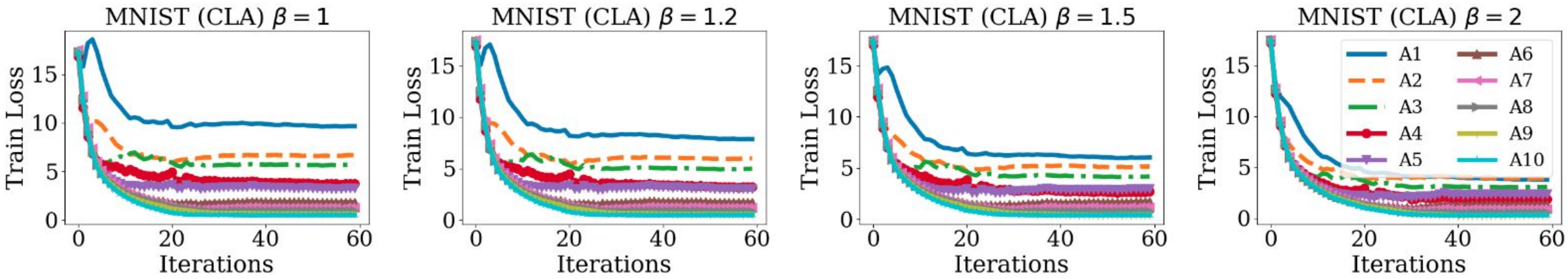
Fairness results

	MNIST						CIFAR-10			MR	SST
No. Agents	10			20			10			5	5
Data Partition	UNI	POW	CLA	UNI	POW	CLA	UNI	POW	CLA	POW	POW
FedAvg	-45.60	55.24	24.12	0.85	-32.58	40.83	18.47	97.48	98.75	48.68	57.50
q-FFL	-44.73	39.00	22.38	-22.01	38.71	48.07	-17.64	51.33	94.06	56.43	-75.92
CFFL	83.57	91.80	81.24	82.52	94.70	85.71	78.25	72.55	81.31	96.85	93.34
ECI	85.26	**99.83**	**99.98**	80.95	**99.41**	95.21	75.85	79.50	99.55	97.69	95.00
DW	89.15	98.93	65.34	86.94	99.63	35.21	-23.14	91.97	45.45	**99.20**	97.12
RR	83.77	71.17	-26.75	-18.64	25.47	95.86	30.67	0.70	90.67	44.16	-25.11
Ours (EU)	84.25	98.25	99.82	80.55	97.77	**99.97**	78.25	94.24	94.95	97.58	93.21
Ours ($\beta = 1$)	94.03	95.74	94.54	84.47	96.39	97.23	**98.80**	**98.78**	**99.89**	96.01	98.20
Ours ($\beta = 1.2$)	94.75	97.28	96.23	90.52	97.72	95.21	91.07	91.59	99.82	96.12	**98.47**
Ours ($\beta = 1.5$)	**96.34**	86.99	95.37	82.68	90.94	98.75	93.55	93.78	95.89	95.32	97.88
Ours ($\beta = 2$)	94.66	91.20	95.38	**96.90**	91.33	94.32	89.80	88.78	93.39	92.22	95.74

Fairness results



Fairness results



Increasing *altruism degree* β “pushes” the training losses of all agents to be more equitably low, and it improves the performance of agents with relatively lower contributions.

Accuracy results (on test set)

	MNIST						CIFAR-10			MR	SST
No. Agents	10			20			10			5	5
Data Partition	UNI	POW	CLA	UNI	POW	CLA	UNI	POW	CLA	POW	POW
Standalone	91 (91)	88 (92)	53 (92)	91 (91)	89 (92)	48 (90)	46 (47)	43 (49)	31 (44)	47(56)	31(34)
FedAvg	93 (94)	92 (94)	53 (93)	93 (93)	92 (94)	49 (92)	48 (48)	47 (50)	32 (47)	51(63)	33(35)
q-FFL	85 (91)	27 (45)	44 (64)	88 (91)	48 (53)	40 (59)	41 (46)	36 (36)	22 (28)	12(18)	23(25)
CFFL	90 (92)	85 (90)	34 (44)	91 (93)	88 (91)	39 (46)	39 (41)	35 (45)	22 (40)	44(53)	31(32)
ECI	94 (94)	92 (94)	53 (94)	94 (94)	92 (94)	49 (92)	49 (49)	47 (51)	31 (46)	56(61)	33(34)
DW	93 (94)	92 (94)	53 (93)	93 (93)	92 (94)	49 (92)	48 (48)	47 (50)	32 (47)	51(62)	33(35)
RR	94 (95)	**95** (95)	64 (72)	94 (95)	94 (95)	50 (56)	47 (59)	49 (51)	26 (29)	**63**(65)	**36**(36)
Ours (EU)	94 (94)	94 (94)	54 (94)	94 (94)	94 (94)	49 (92)	49 (49)	49 (51)	32 (46)	54(59)	34(36)
Ours ($\beta = 1$)	96 (97)	94 (95)	74 (**95**)	95 (96)	96 (97)	65 (93)	61 (**62**)	**60** (**62**)	35 (**54**)	62(**76**)	35(36)
Ours ($\beta = 1.2$)	94 (95)	**95** (95)	**75** (**95**)	96 (96)	**96** (**97**)	65 (93)	61 (**62**)	**60** (**62**)	35 (**54**)	62(75)	34(**37**)
Ours ($\beta = 1.5$)	**97** (**97**)	**95** (95)	**75** (**95**)	**96** (**97**)	94 (95)	65 (93)	61 (**62**)	59 (**62**)	35 (**54**)	62(74)	35(**37**)
Ours ($\beta = 2$)	96 (96)	**95** (**96**)	73 (94)	**97** (**97**)	95 (96)	**66** (**95**)	**62** (**62**)	**61** (**62**)	**36** (**54**)	62(75)	35(**37**)

Average (maximum) test accuracies over all agents.

Runtime results

	MNIST			CIFAR-10		MR	SST
No. Agents	5	10	20	5	10	5	5
FedAvg	1.17 (7e-3)	1.05 (1e-2)	4.29 (1e-2)	1.66 (7e-3)	7.41 (1e-2)	1.3 (1e-4)	1.31 (6e-4)
q-FFL	6.14 (4e-2)	4.97 (5e-2)	91.20 (0.3)	97.28 (0.4)	58.94 (7e-2)	90.01 (8e-3)	82.85 (4e-2)
CFFL	32.15 (0.2)	21.79 (0.3)	500.03 (1.6)	570.12 (2.0)	302.44 (0.4)	479.12 (0.2)	487.71 (2e-1)
ECI	2377.33 (16)	11937.80 (141)	23749.06 (74)	3571.75 (15)	58835.83 (84)	422.85 (4e-2)	801.20 (0.4)
DW	**0.89 (6e-3)**	**0.79 (9e-3)**	**1.60 (5e-3)**	**1.21 (5e-3)**	**5.29 (7e-3)**	**0.99 (1e-5)**	0.98 (5e-4)
RR	**0.89 (6e-3)**	0.82 (9e-3)	**1.60 (5e-3)**	3.31 (1e-2)	5.41 (7e-3)	1.01 (5e-4)	**0.99 (5e-4)**
Ours (EU)	**0.89 (6e-3)**	0.81 (9e-3)	1.61 (5e-3)	1.22 (5e-3)	5.33 (7e-3)	1.01 (5e-4)	**0.99 (5e-4)**
Ours (Cosine)	6.34 (4e-2)	4.94 (5e-2)	94.30 (0.3)	98.39 (0.4)	54.94 (7e-2)	89.81 (8e-3)	82.87 (4e-2)

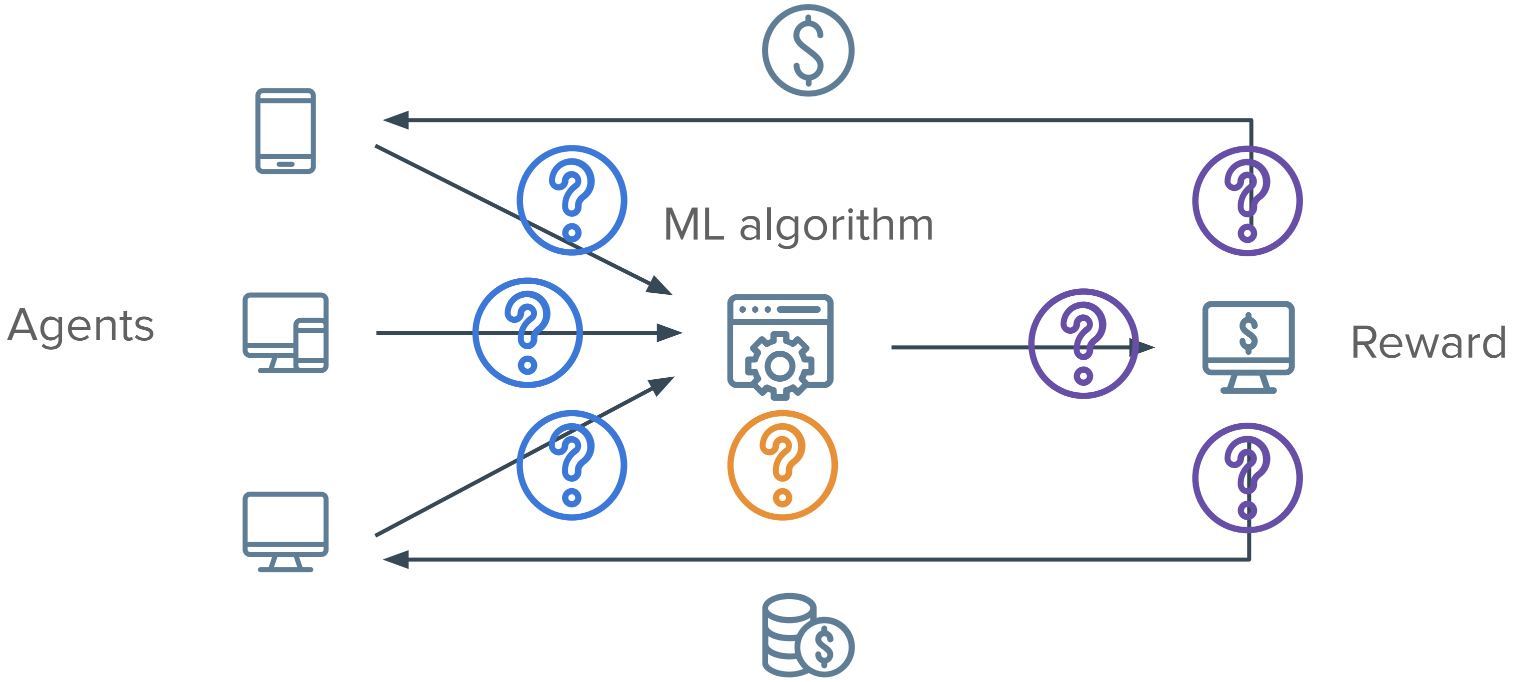
Number of seconds (ratio w.r.t. training time).

Discussion

Fairness in rewards in action

- Each agent's interest is protected, i.e., they get **rewarded** commensurately with their **contributions** measured in **Shapley values**.
- Flexibly control the proportionality between **rewards** and **contributions**, via β.
- Computational overhead at server is small.

Collaborative Machine Learning (CML)



Latest Publications

	ML Algorithm	Resource	Desiderata
NeurIPS'21 Fair CML	gradient descent	functionals of data	fairness and training-time rewards
NeurIPS'21 Volume	ML model agnostic	statistics of data	fairness, replication robustness
AAAI'22	generative modeling	statistics of data (distributional divergence)	fairness, synthetic data generation
ICML'22	Bayesian parameter learning	statistics of data (Fisher information)	asymptotic fairness

- IJCAI-ECAI2022 - Survey on Data Valuation
  - Use cases: interpretable ML, active learning, adversarial data detection
  - Data valuation principles and desiderata

Thank you!