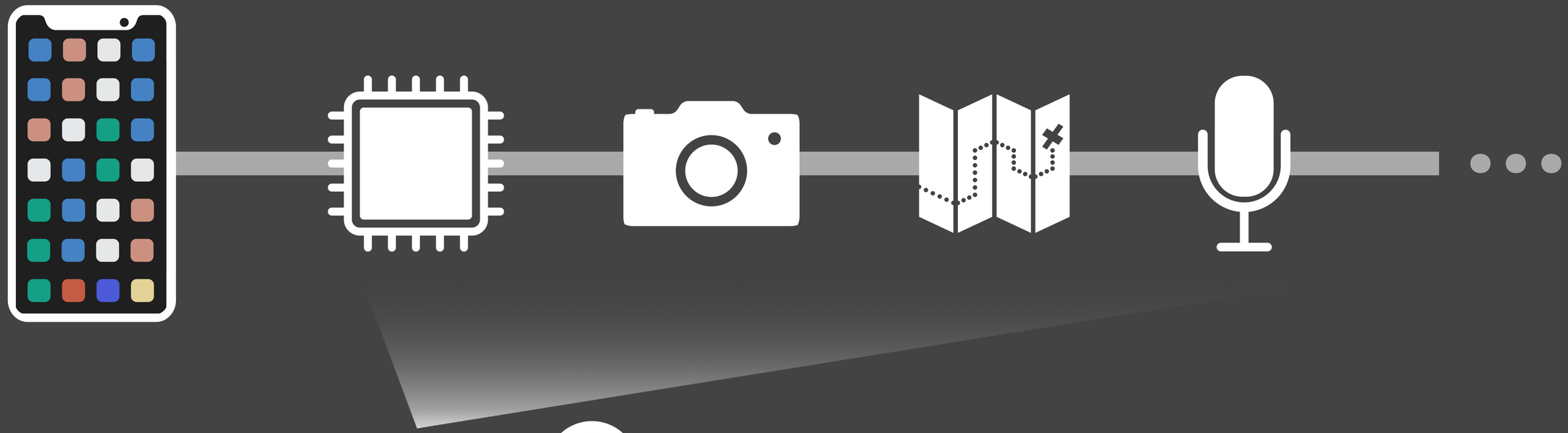
INFOCOM’20

Optimizing Federated Learning on Non-IID Data with Reinforcement Learning

Hao Wang*, Zakhary Kaplan*, Di Niu^, Baochun Li*

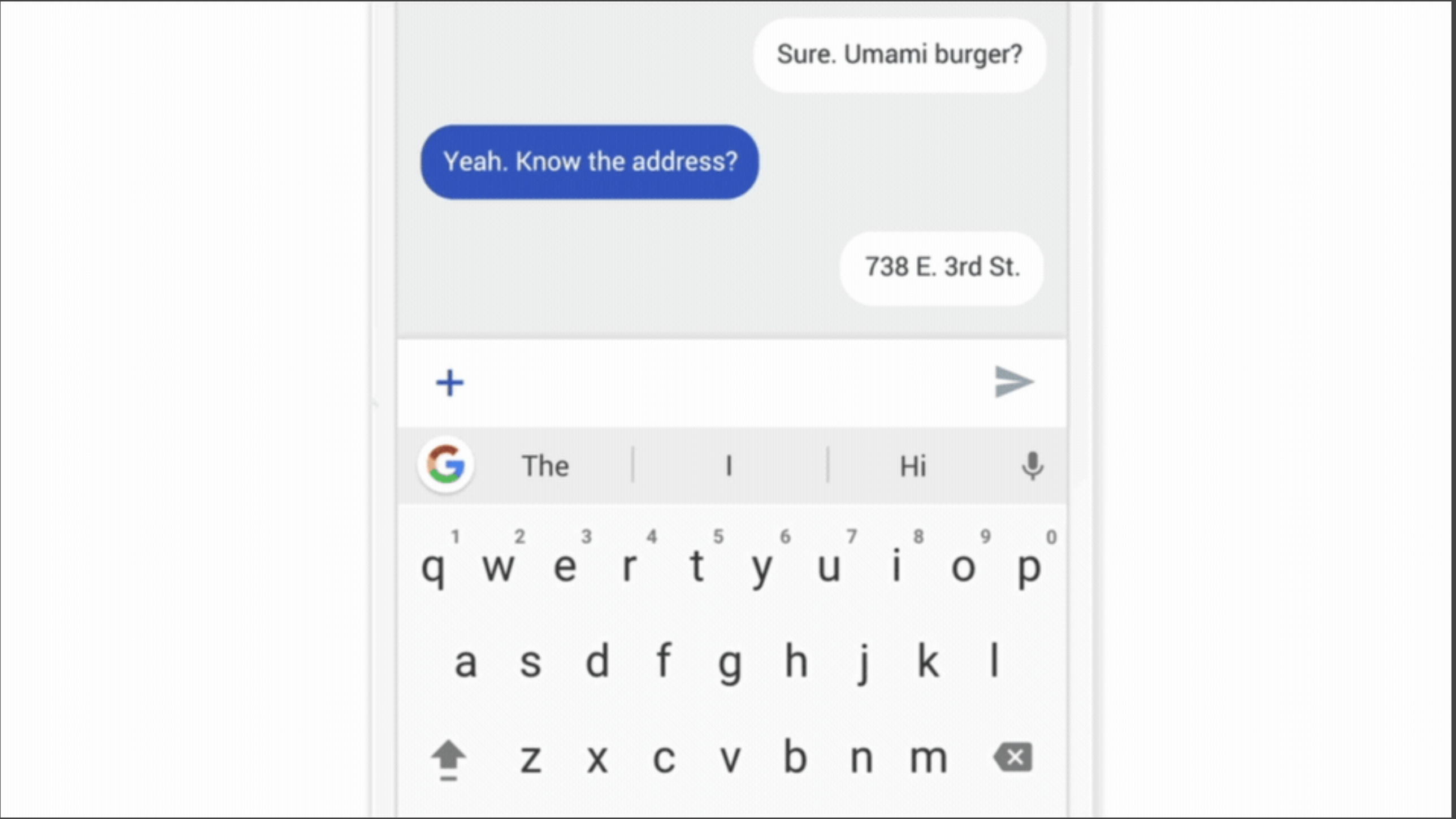
*University of Toronto, ^University of Alberta



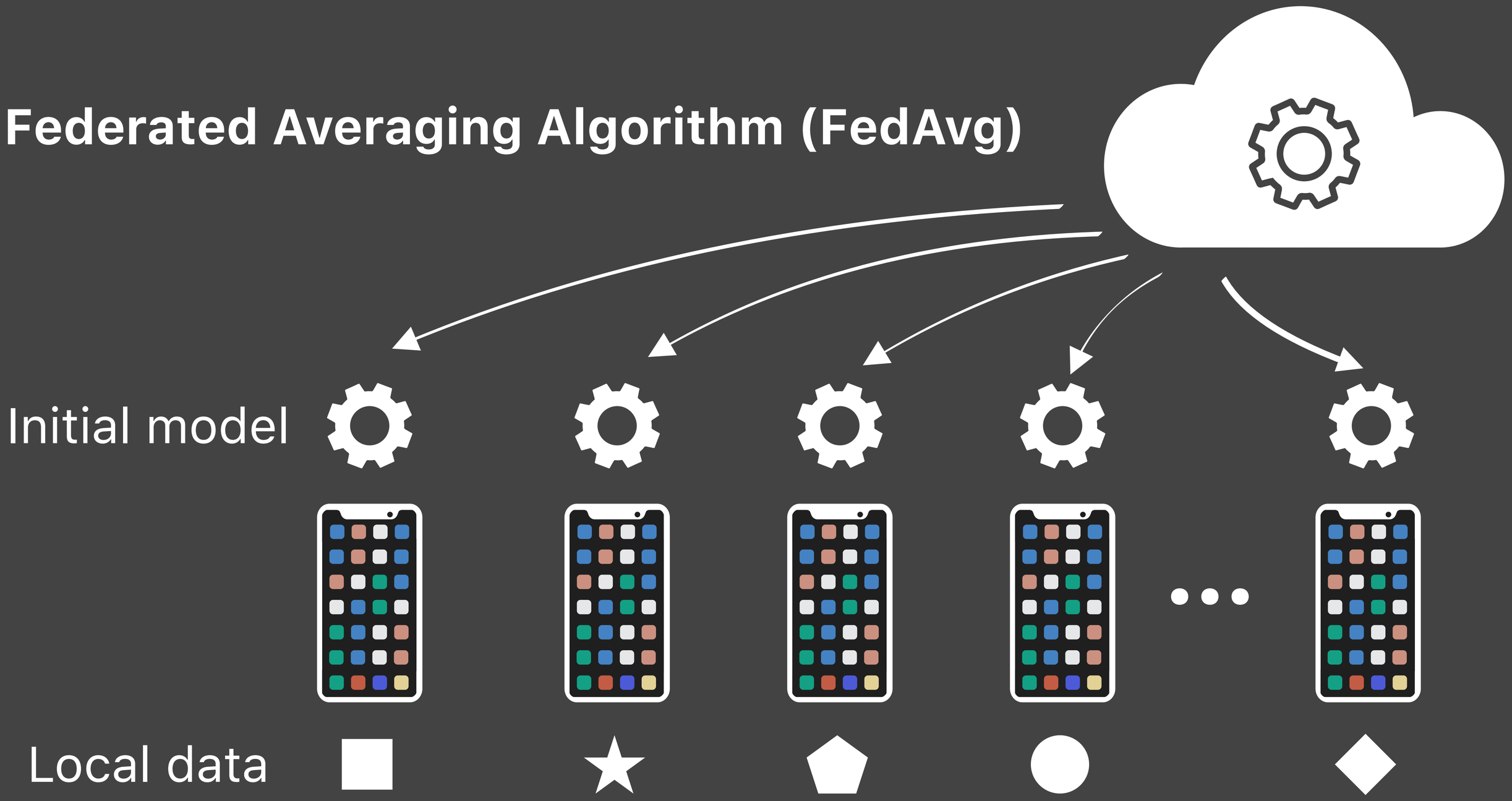
Siri

Alexa

Federated Learning

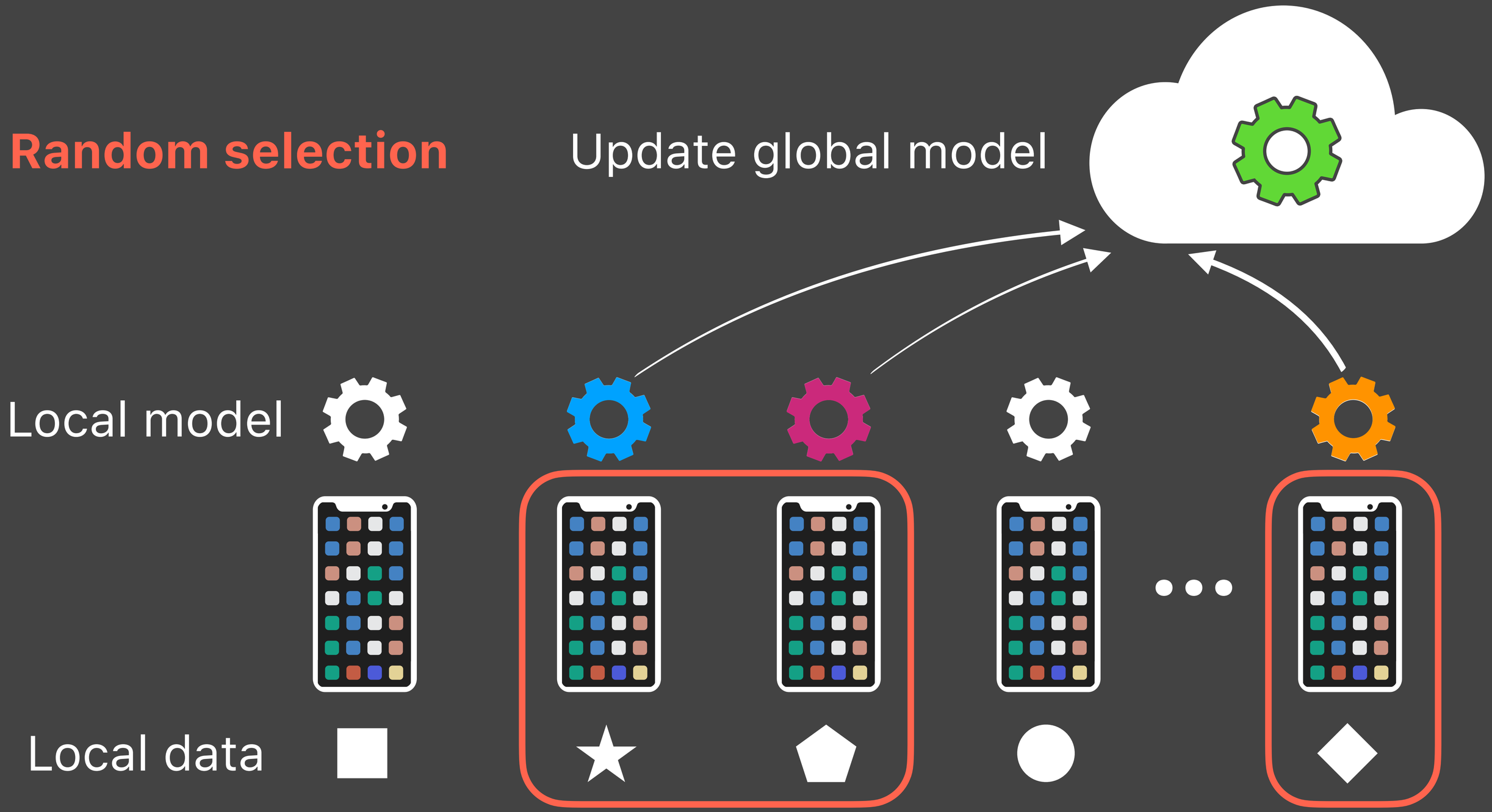

Sure. Umami burger?
Yeah. Know the address?
738 E. 3rd St.
The
I
Hi
q w e r t y u i o p
a s d f g h j k l
z x c v b n m

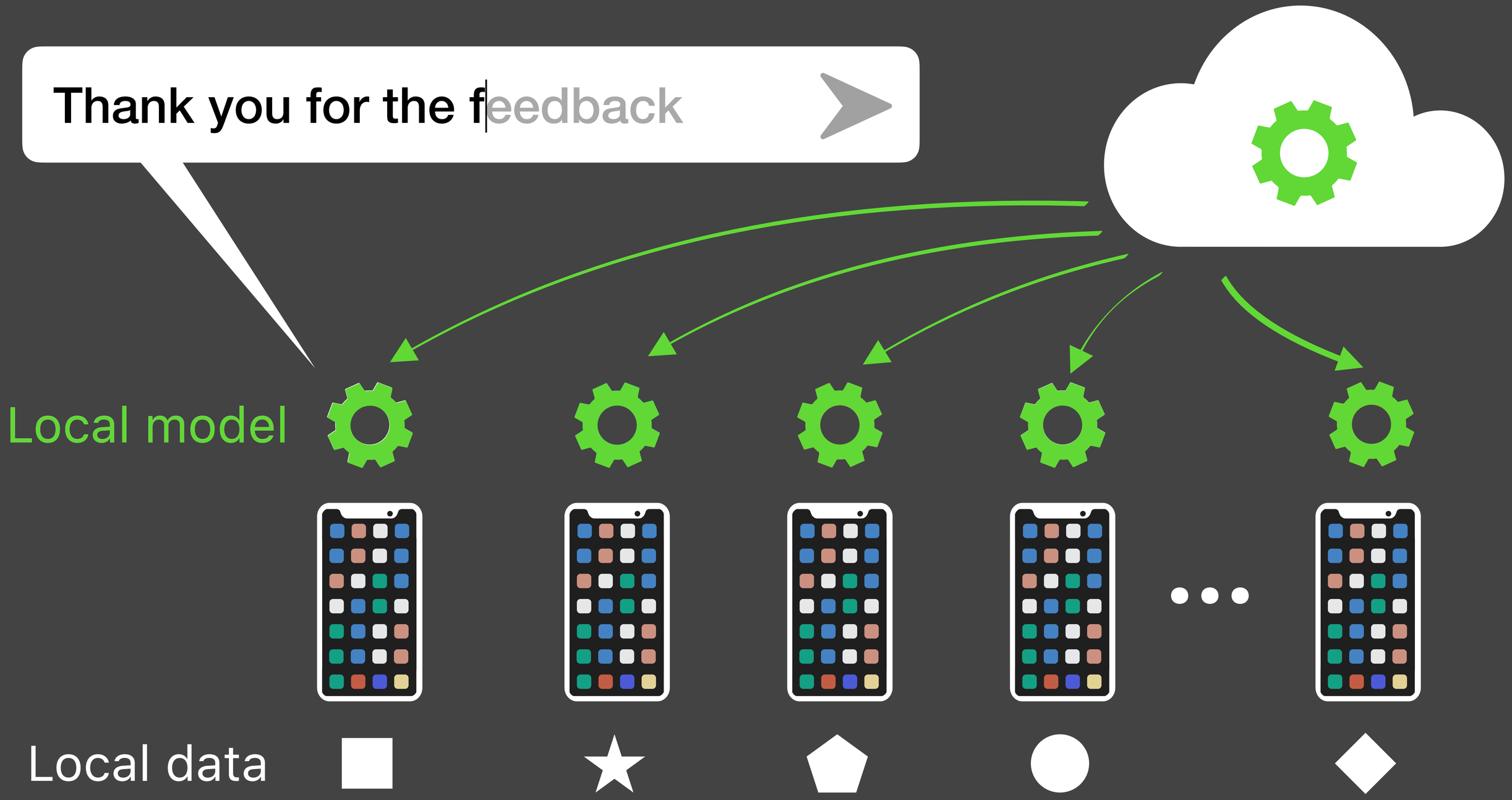
Federated Averaging Algorithm (FedAvg)



Random selection

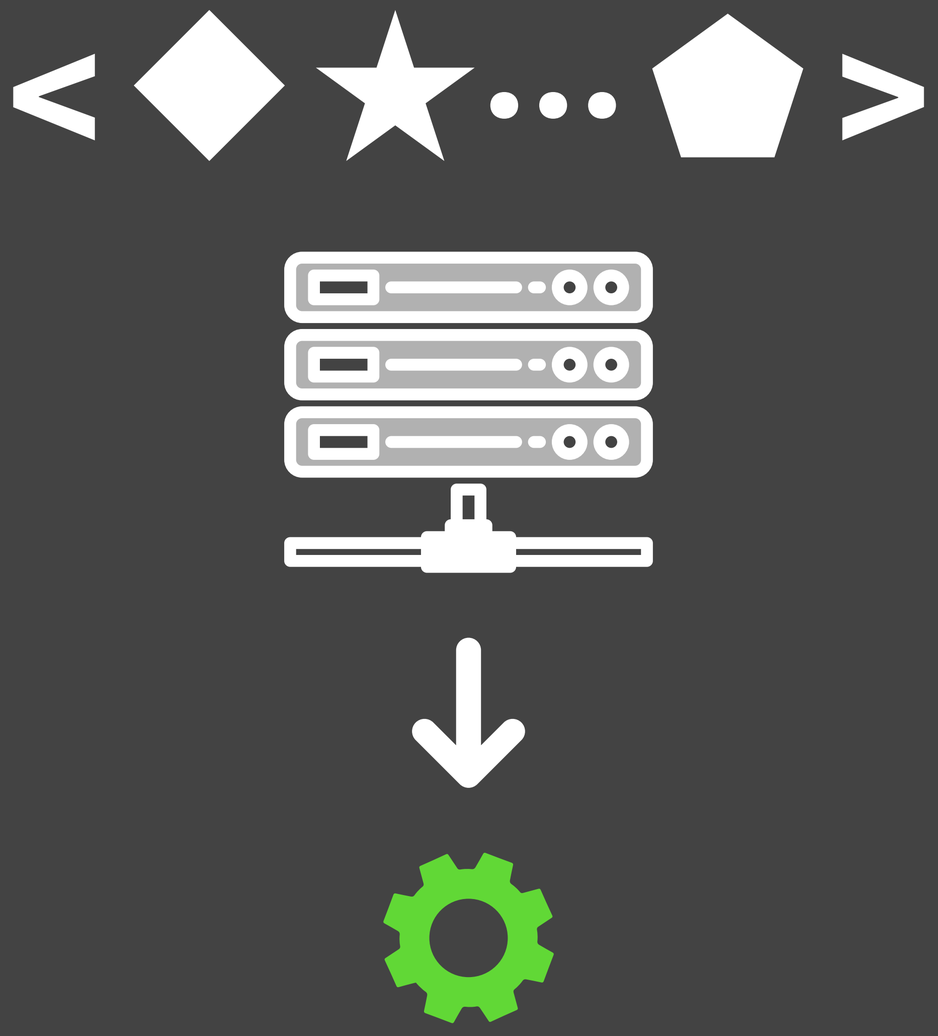
Update global model

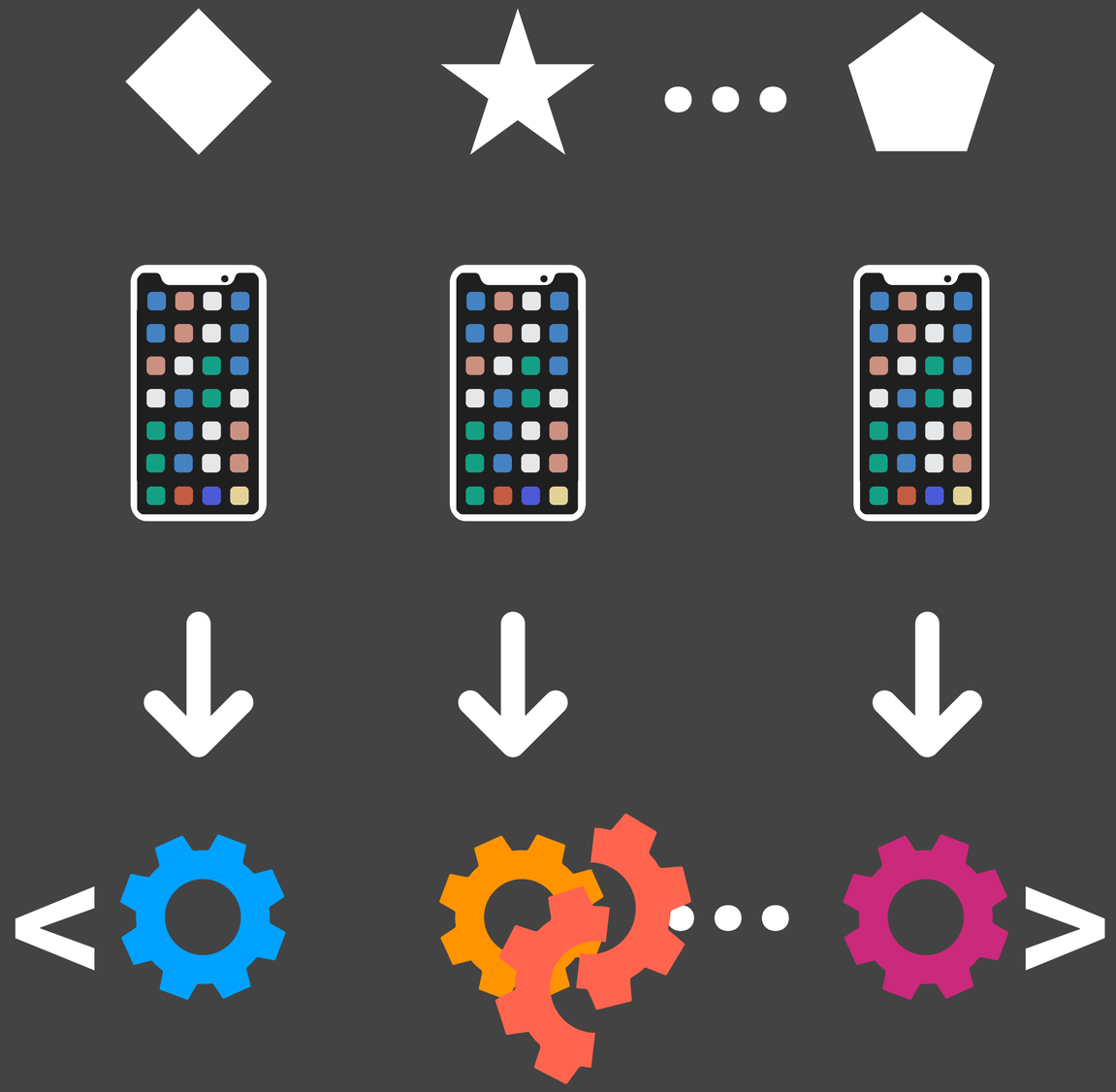



Thank you for the feedback
Local model
Local data

ML algorithms assume the training data is **independent and identically distributed (IID)**

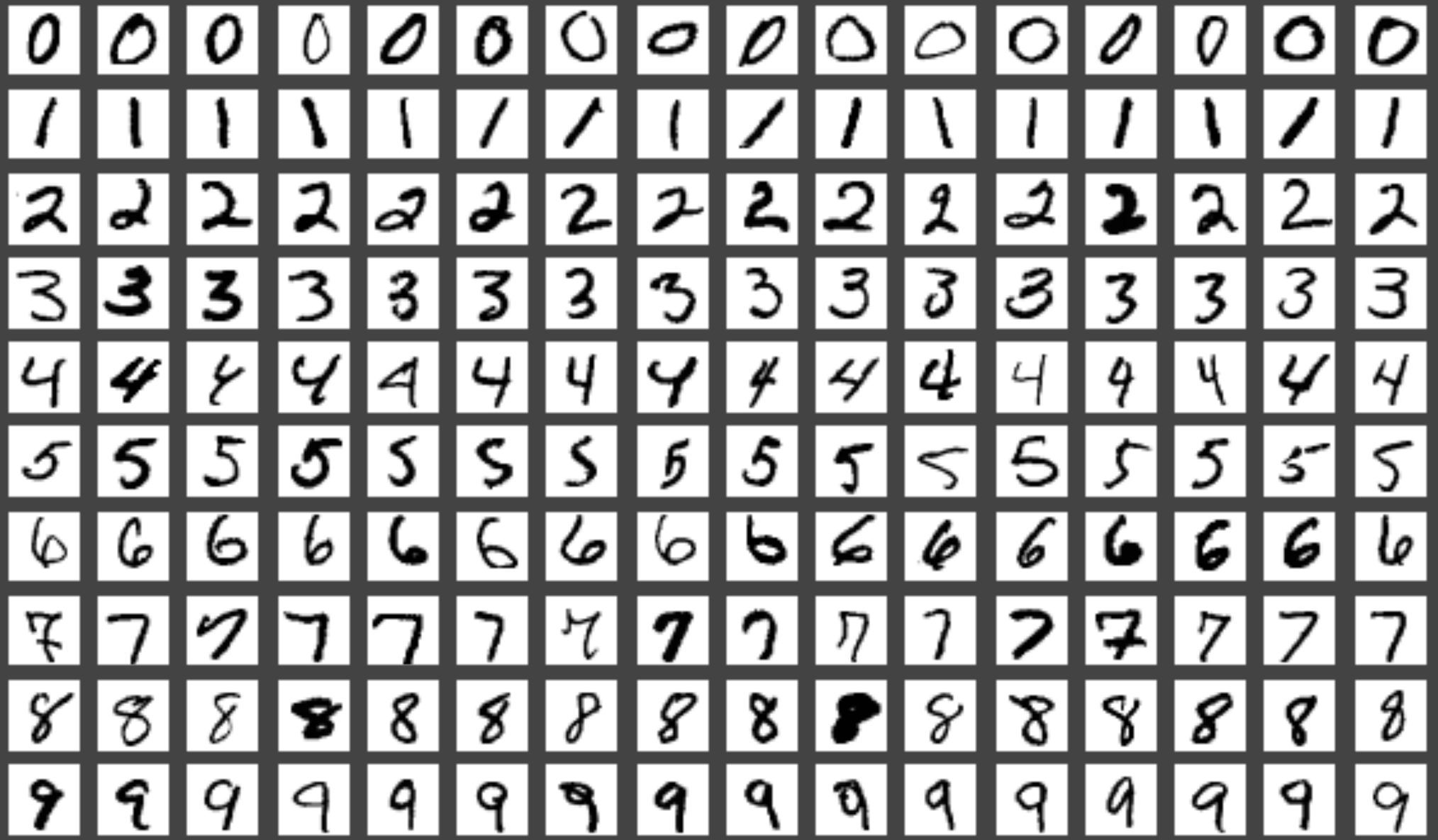
Federated Learning reuses the existing ML algorithms but on **non-IID data**



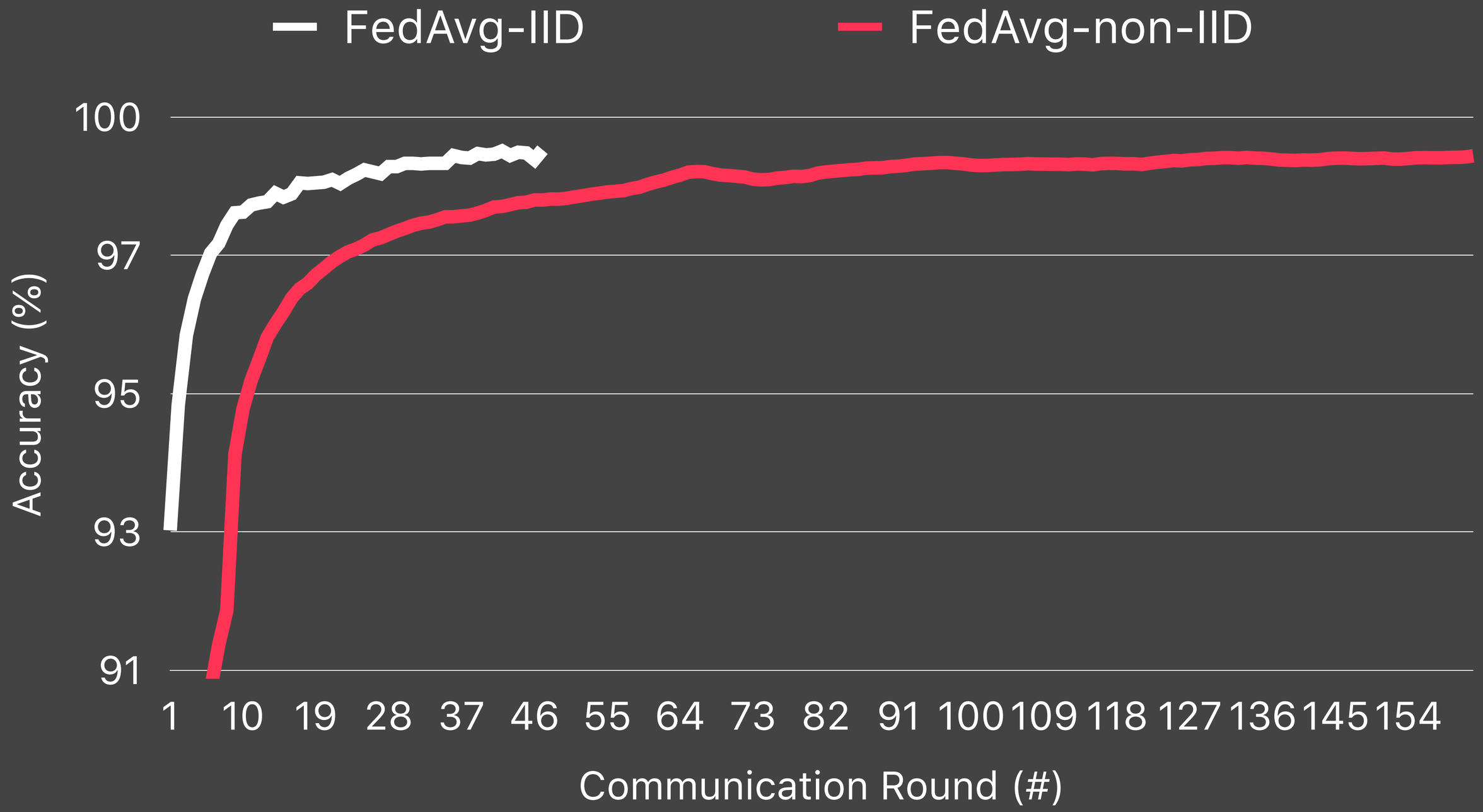


Non-IID data introduces bias into the training and leads to **a slow convergence** and **training failures**

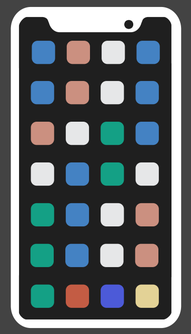
MNIST



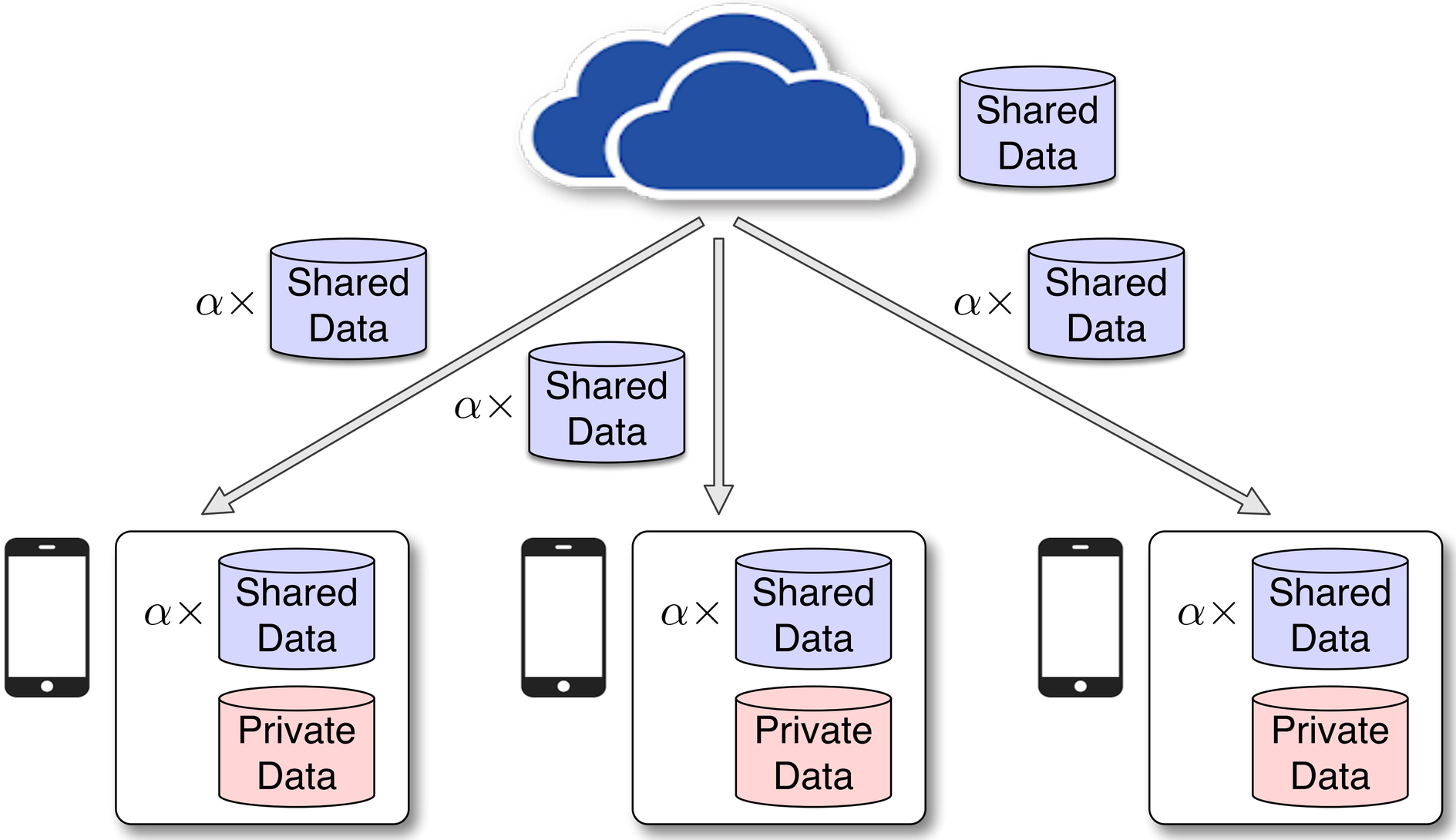
http://yann.lecun.com/exdb/mnist/


FedAvg-IID
FedAvg-non-IID
100
97
95
93
91
Accuracy (%)
1
10
19
28
37
46
55
64
73
82
91
100
109
118
127
136
145
154
Communication Round (#)

Build IID training data?



No, we **don’t have any access** to the data on your phone.



Zhao, Yue, et al. "Federated Learning with Non-IID Data." arXiv preprint arXiv:1806.00582 (2018).

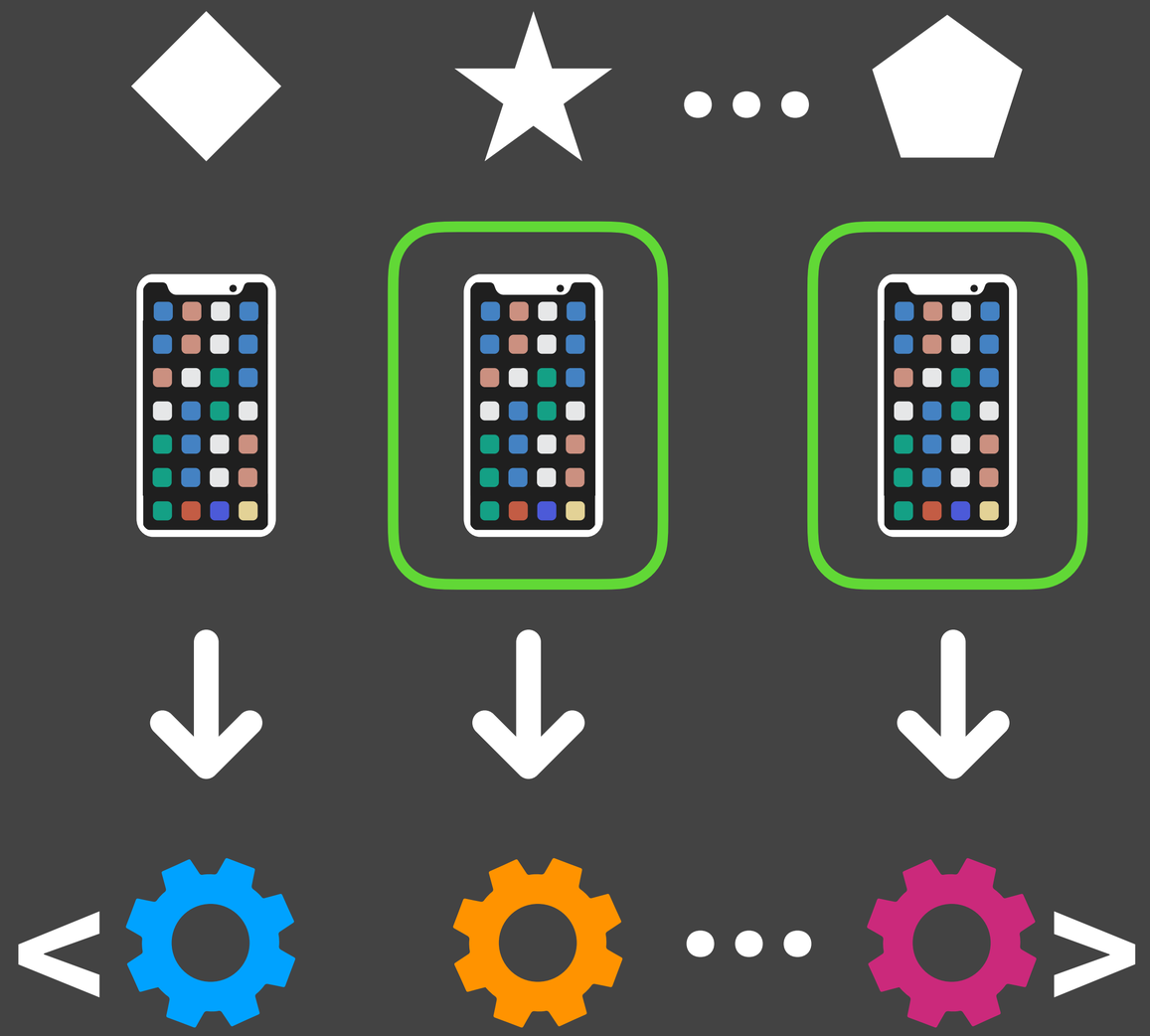
Optimizing Federated Learning on Non-IID Data with Reinforcement Learning

[INFOCOM'20]

Build IID training data? **No**

Peeking into the data distribution on each device without violating data privacy

Probing the bias of non-IID data



Carefully **select devices** to **balance** the bias introduced by **non-IID data**

Probing the data distribution

100 devices, each has 600 samples

Non-IID data

80% data has the same label, e.g, “6”

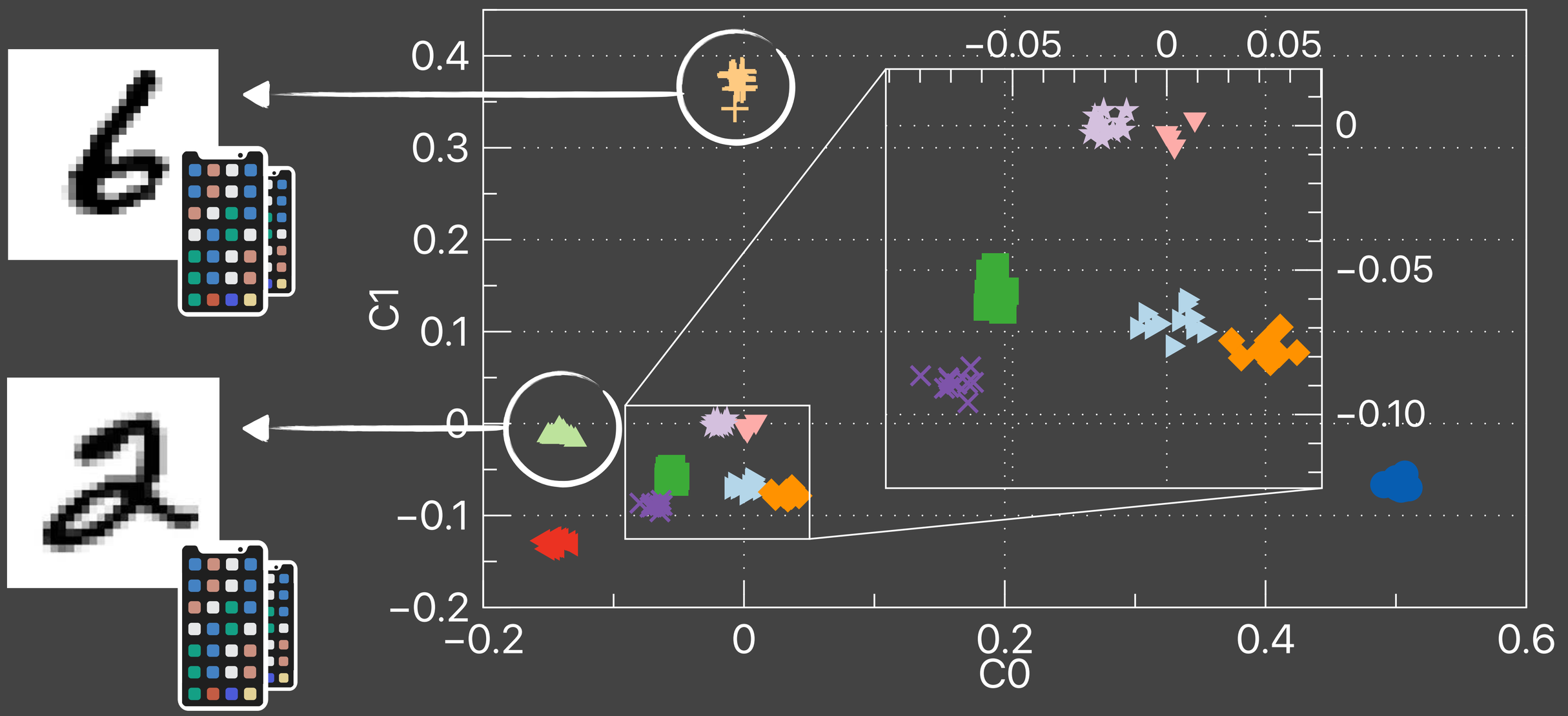
Initial model

A two-layer CNN model with
431,080 parameters

Local model

We apply **Principle Component Analysis (PCA)** to reduce dimensionality

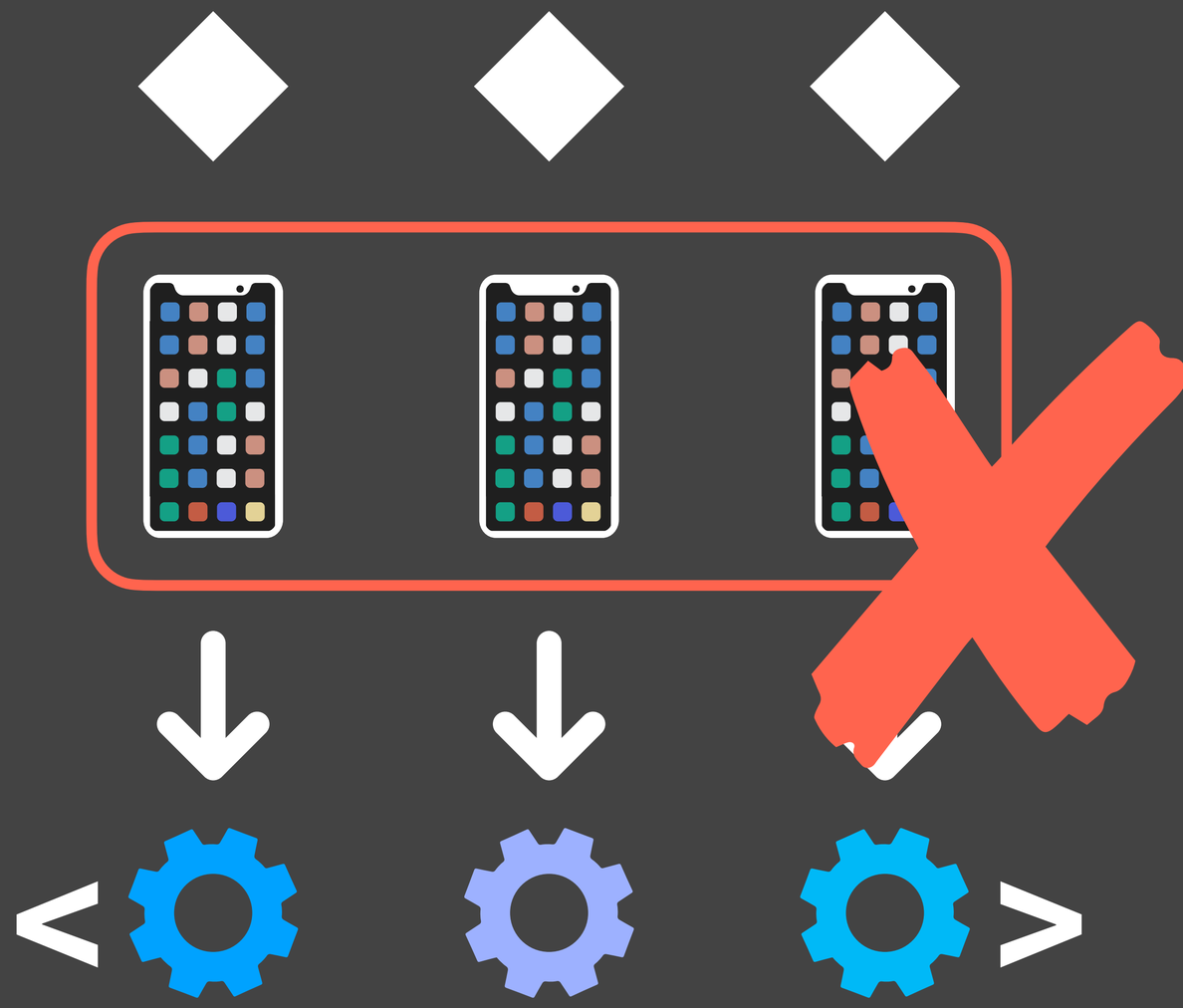
431,080-dimension model weight → 2-dimension space

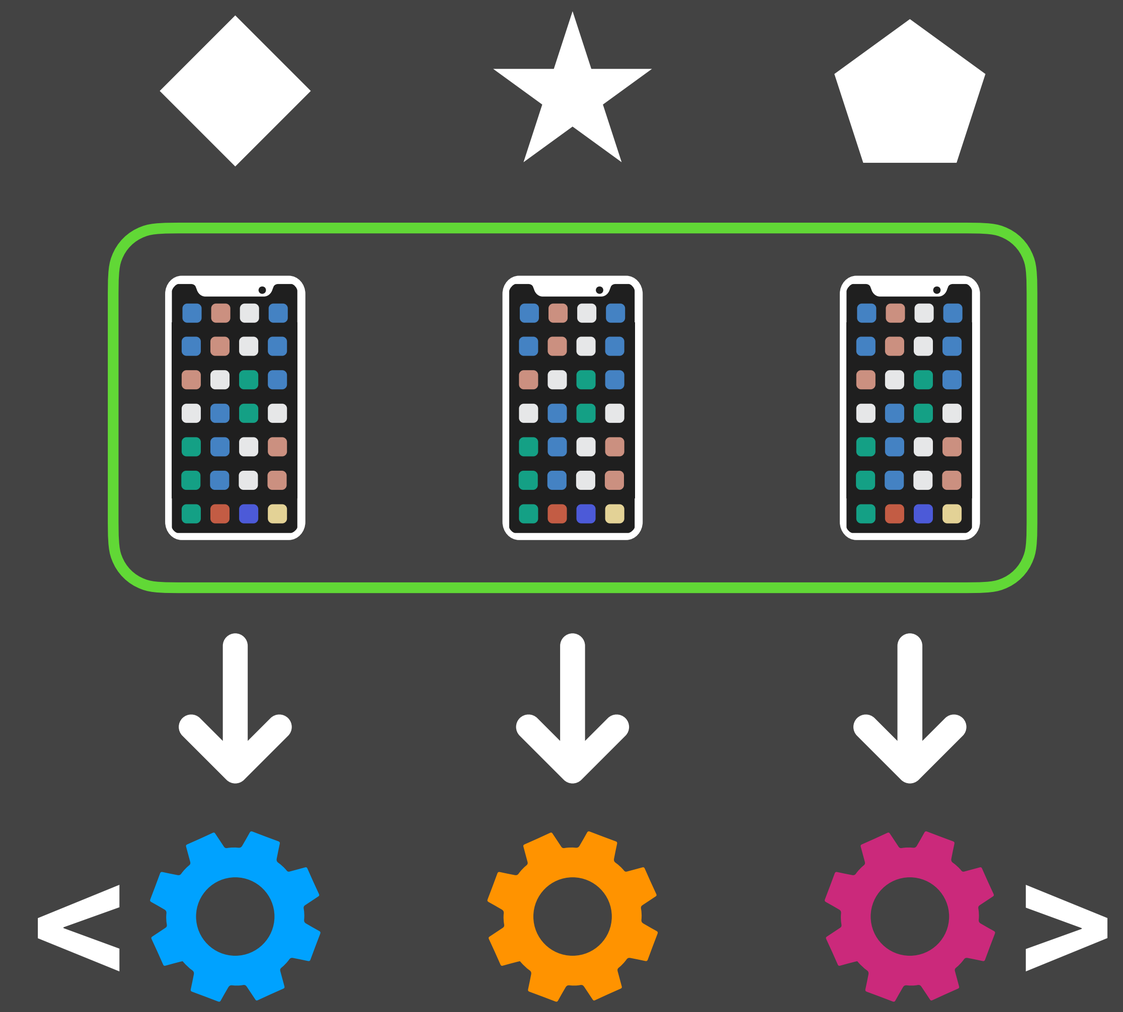

0.4
0.3
0.2
0.1
0
−0.1
−0.2
C1
−0.2
0
0.2
0.4
0.6
C0
−0.05
0
0.05
0
−0.05
−0.10

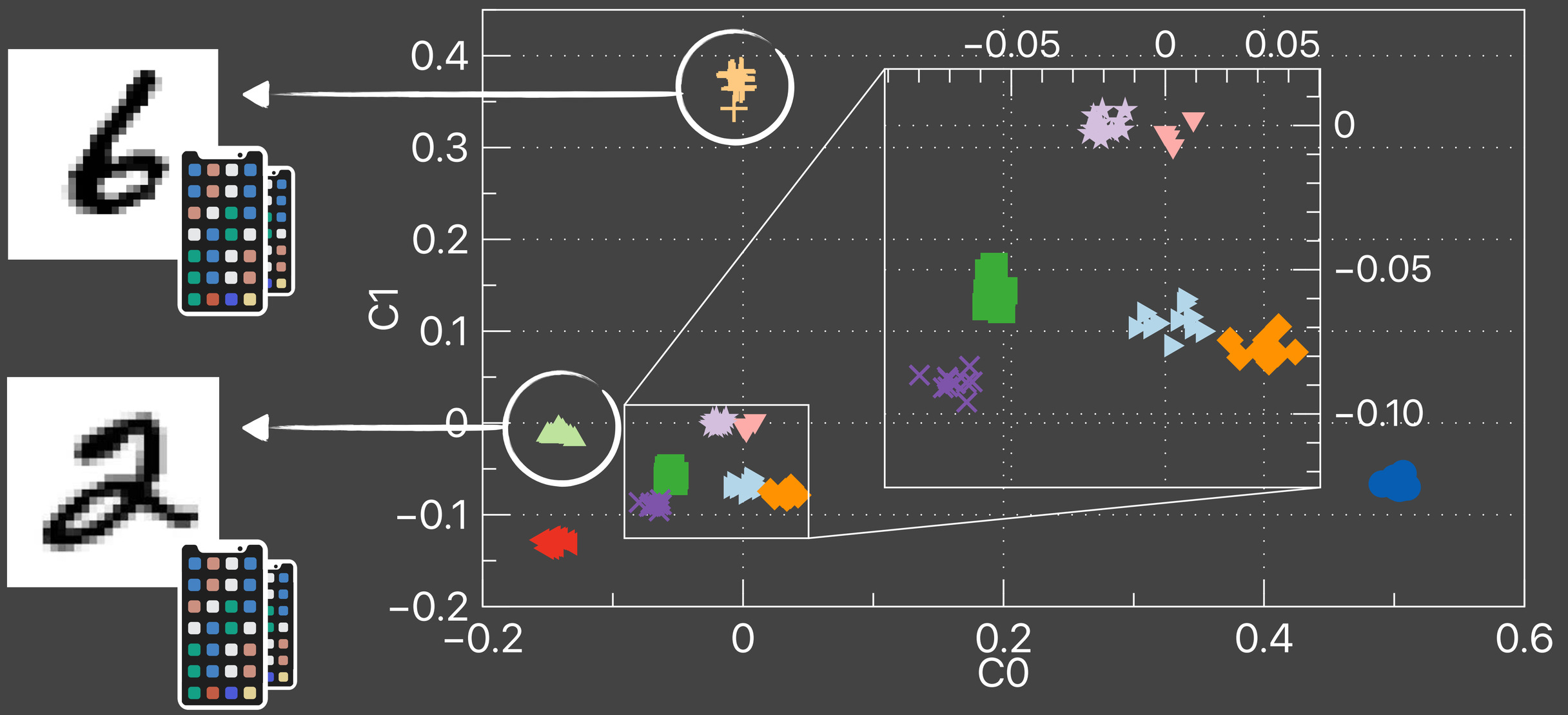
An **implicit connection** between
model weights and **data distribution**

Probing the data distribution

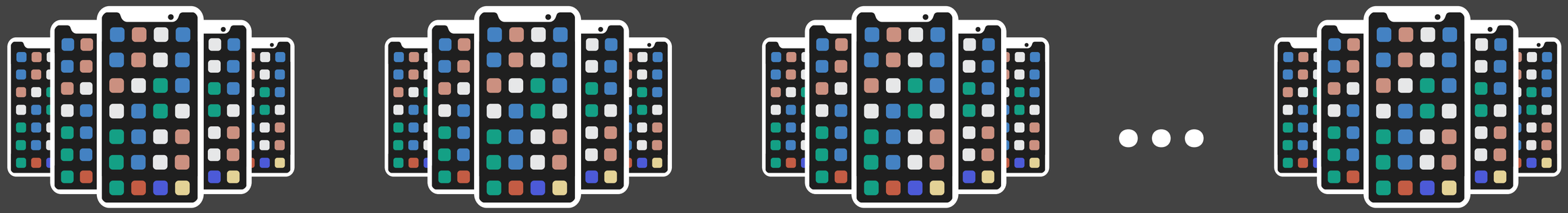
Selecting devices for federated learning



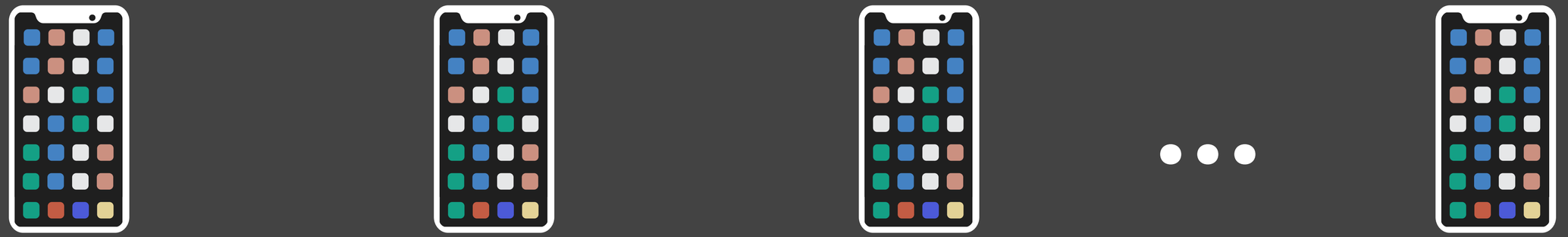


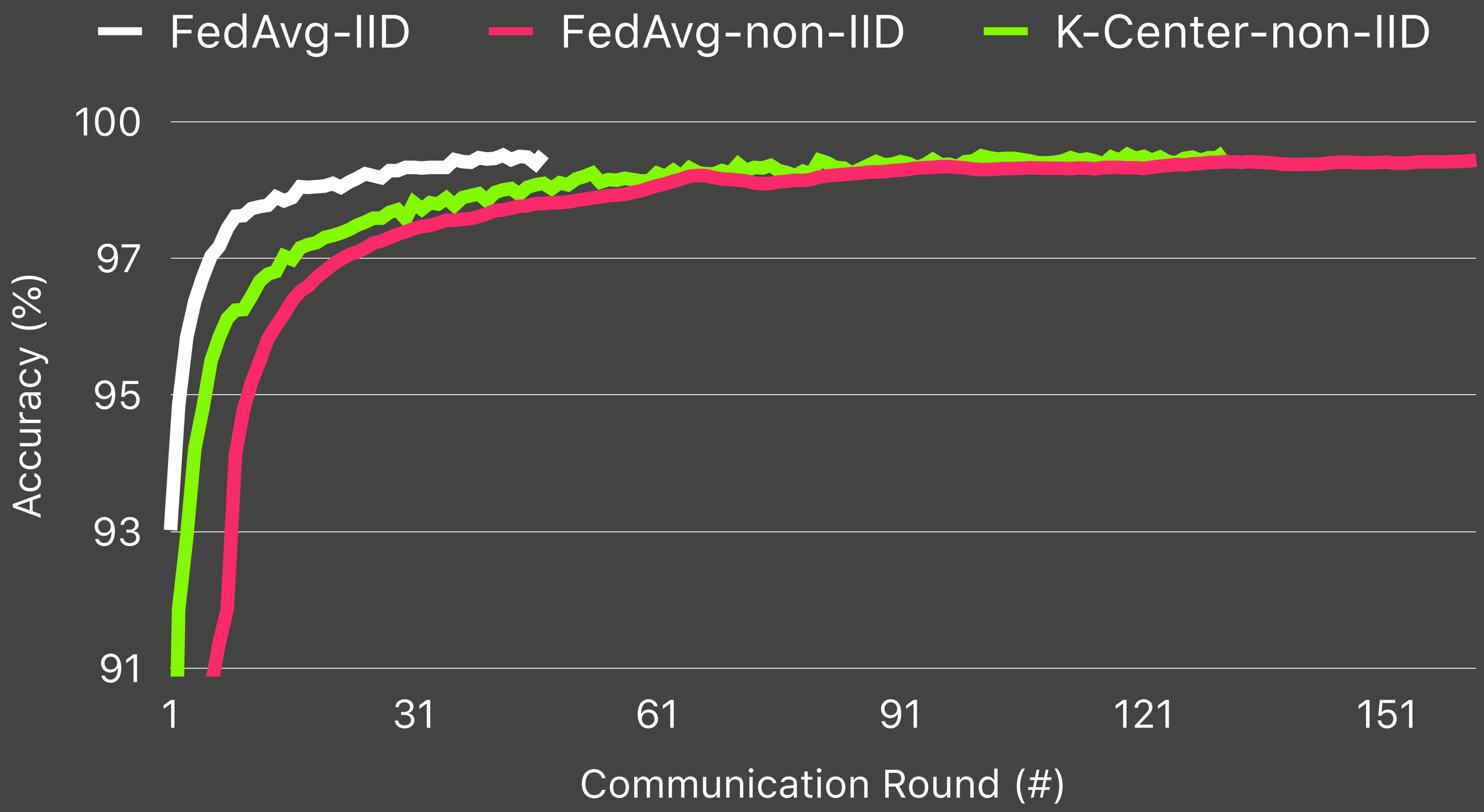

0.4
0.3
0.2
0.1
0
−0.1
−0.2
C1
−0.2
0
0.2
0.4
0.6
C0
−0.05
0
0.05
0
−0.05
−0.10

K-Center Clustering



Random Selection from Groups




FedAvg-IID
FedAvg-non-IID
K-Center-non-IID
100
97
95
93
91
Accuracy (%)
1
31
61
91
121
151
Communication Round (#)

Probing the data distribution

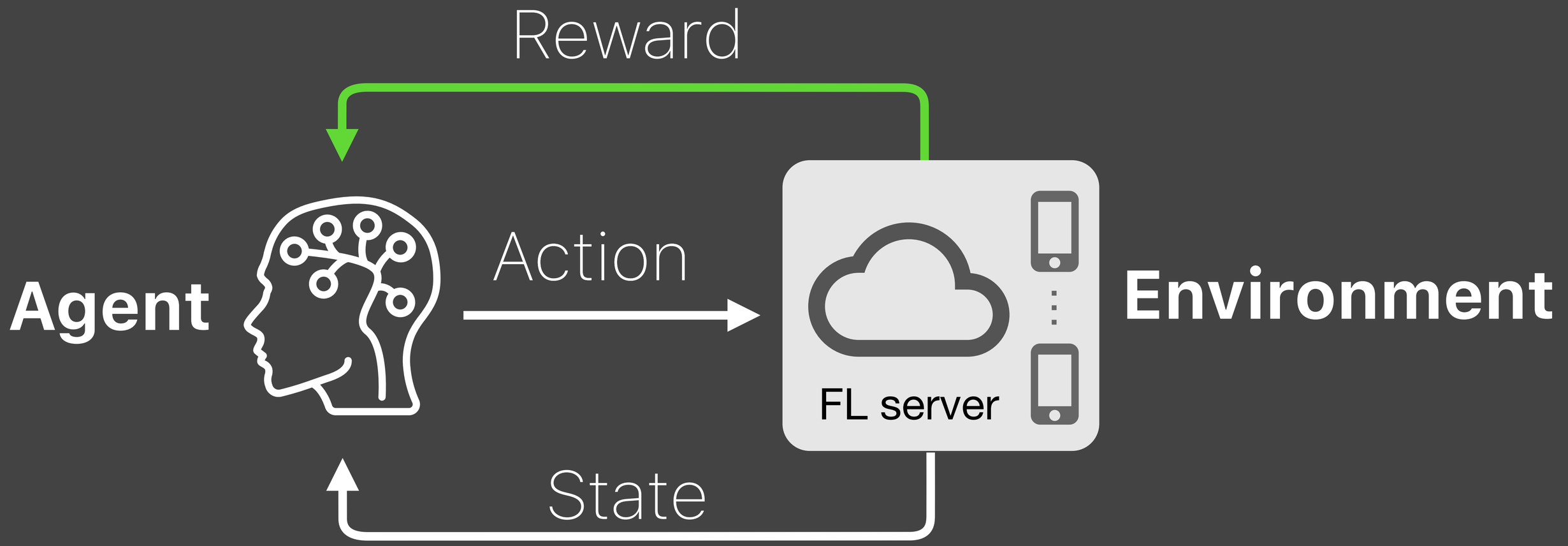
Selecting devices for federated learning

How to select devices to speed up training ?

It is difficult to select the appropriate subset of devices

- Model weights —> device selection choice
- A dynamic and undeterministic problem

Reinforcement Learning (RL)



(…,state, action, reward, state', action', …,end)

Episode

(…,state, action, reward, state′, action′, …,end)

(…,state, action, reward, state′, action′, …,end)

(…,state, action, reward, state′, action′, …,end)

(…,state, action, reward, state′, action′, …,end)

(…,state, action, reward, state′, action′, …,end)

(…,state, action, reward, state′, action′, …,end)

⋮

(…,state, action, reward, state′, action′, …,end)

(…,state, action, reward, state′, action′, …,end)

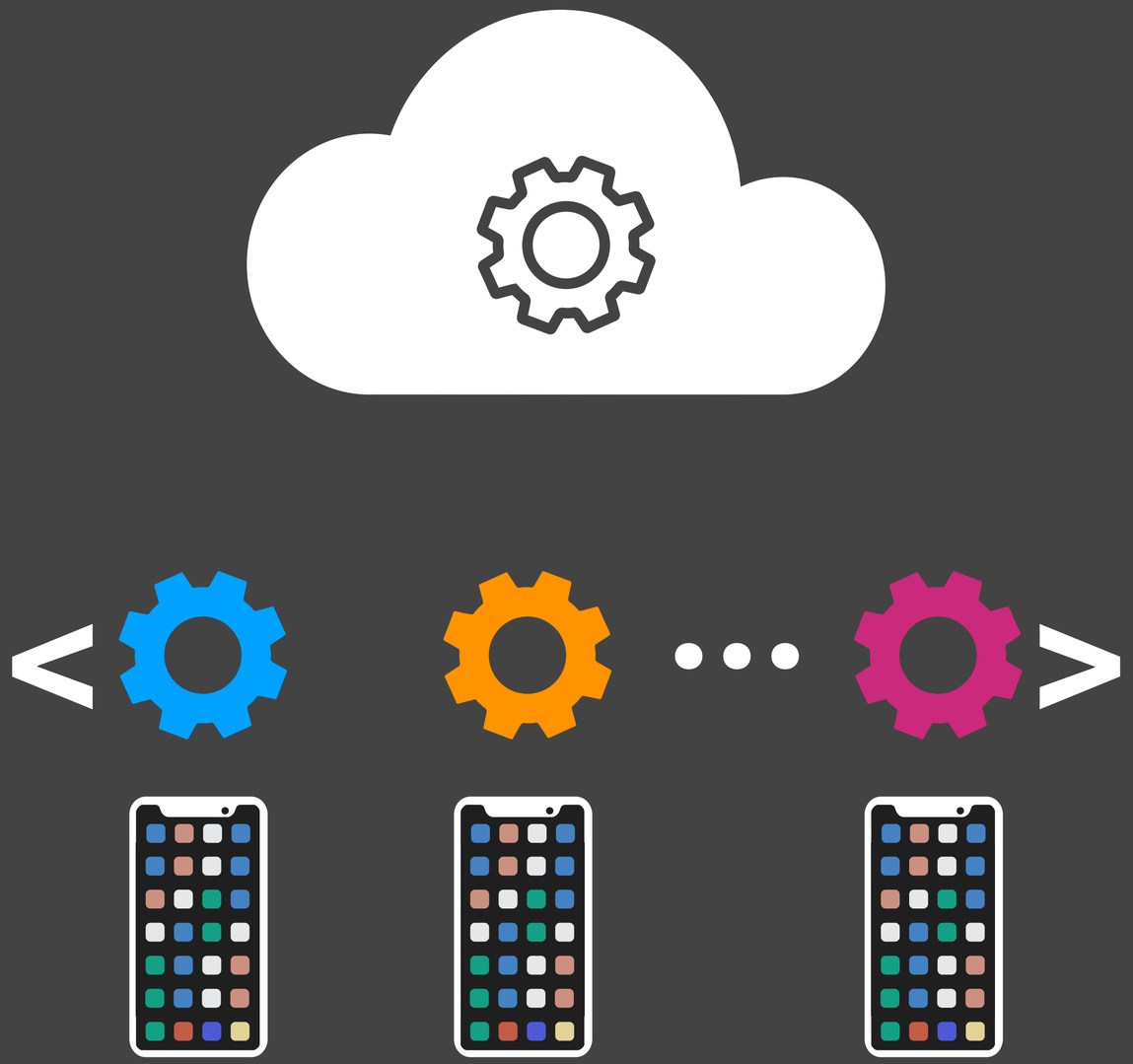
(…,state, action, **reward**, state', action', …,end)
(…,state, action, **reward**, state', action', …,end)
(…,state, action, **reward**, state', action', …,end)

Learn to maximize `sum(reward)`

⋮

(…,state, action, **reward**, state', action', …,end)
(…,state, action, **reward**, state', action', …,end)

States



Global weights

Local model weights

100-dimension vector

Actions

Select K devices from a pool of N devices — a huge action space

Selecting 10 devices from a pool of 100 devices leads to

1.7310309e+13 possible actions

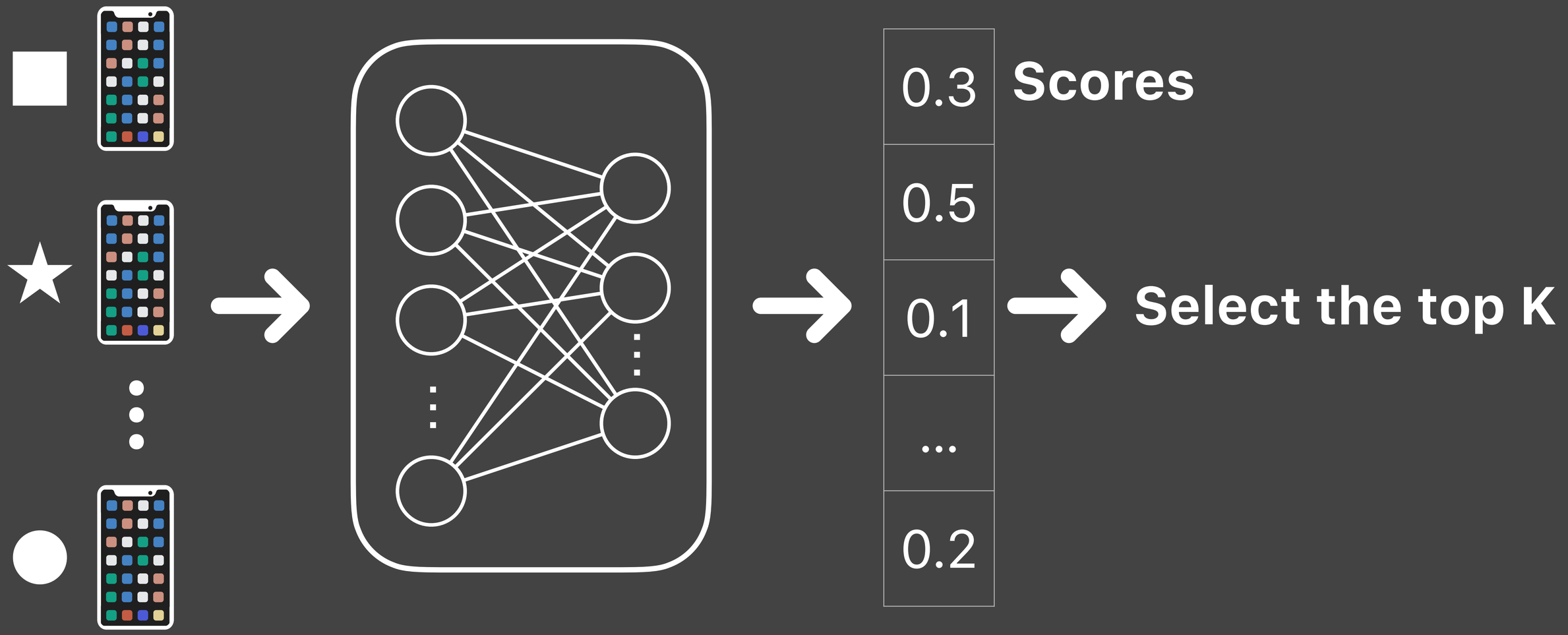
Modify the RL training algorithm

Selecting the Top K Devices

Only one device is selected during the RL training

Now the action space is **{1, 2, ..., N}**, instead of selecting K devices from N devices

Evaluating Each Device



Rewards

$$r_t = \Xi^{(\omega_t - \Omega)} - 1$$

$$0 \leqslant \omega_t \leqslant \Omega \leqslant 1$$

$$r_t \in (-1, 0]$$

Ξ	Positive constant
ω_t	Training Accuracy
Ω	Target accuracy
t	Communication round #

👍 **Accuracy increase: ω_t⬆ —> r_t⬆**

👎 **More communication rounds: t⬆ —> sum(r_t)⬇**

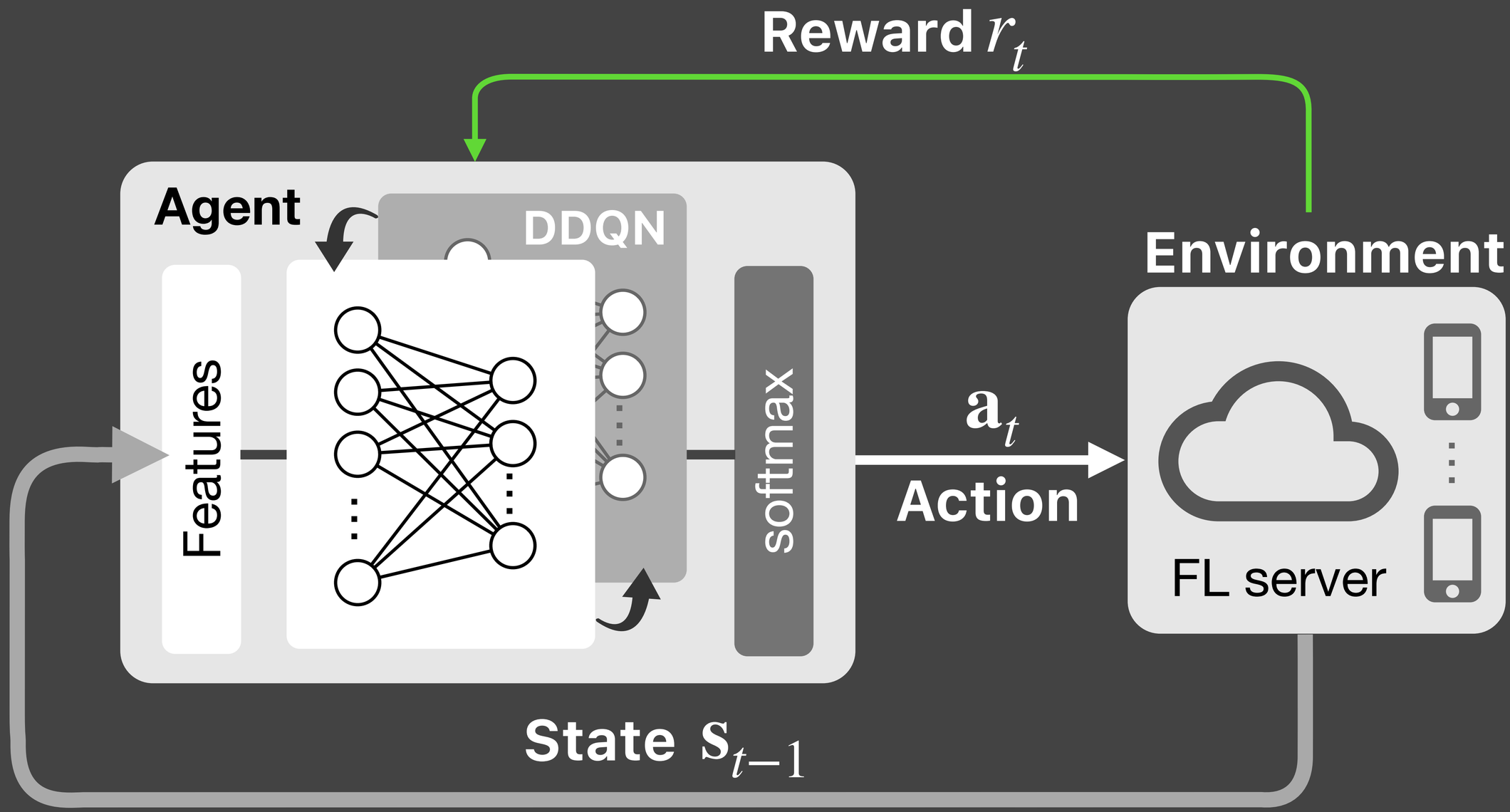
Training the DRL Agent

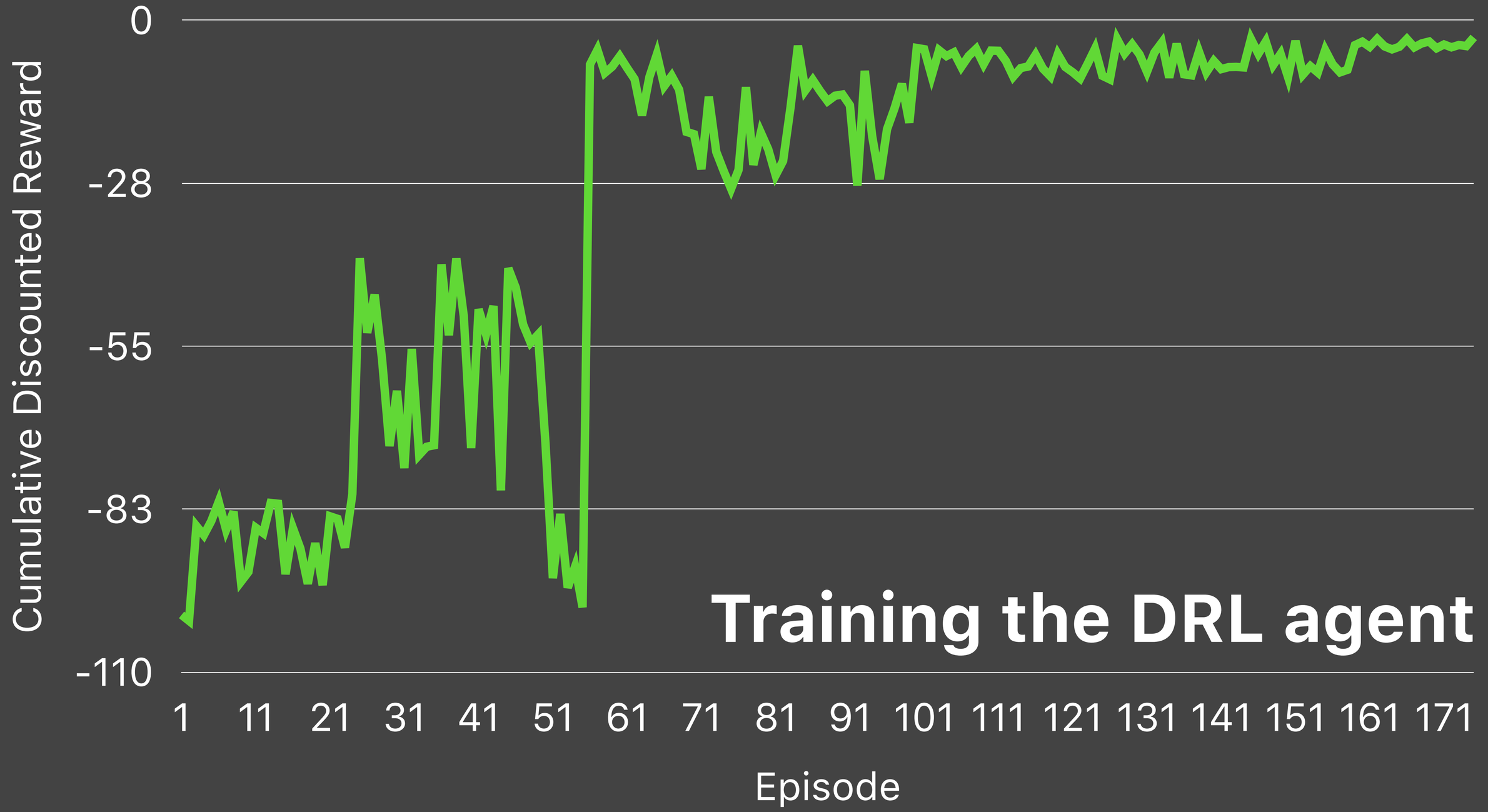
Look for a **function** that points out the **actions** leading to the maximum cumulative **return** under a particular **state**

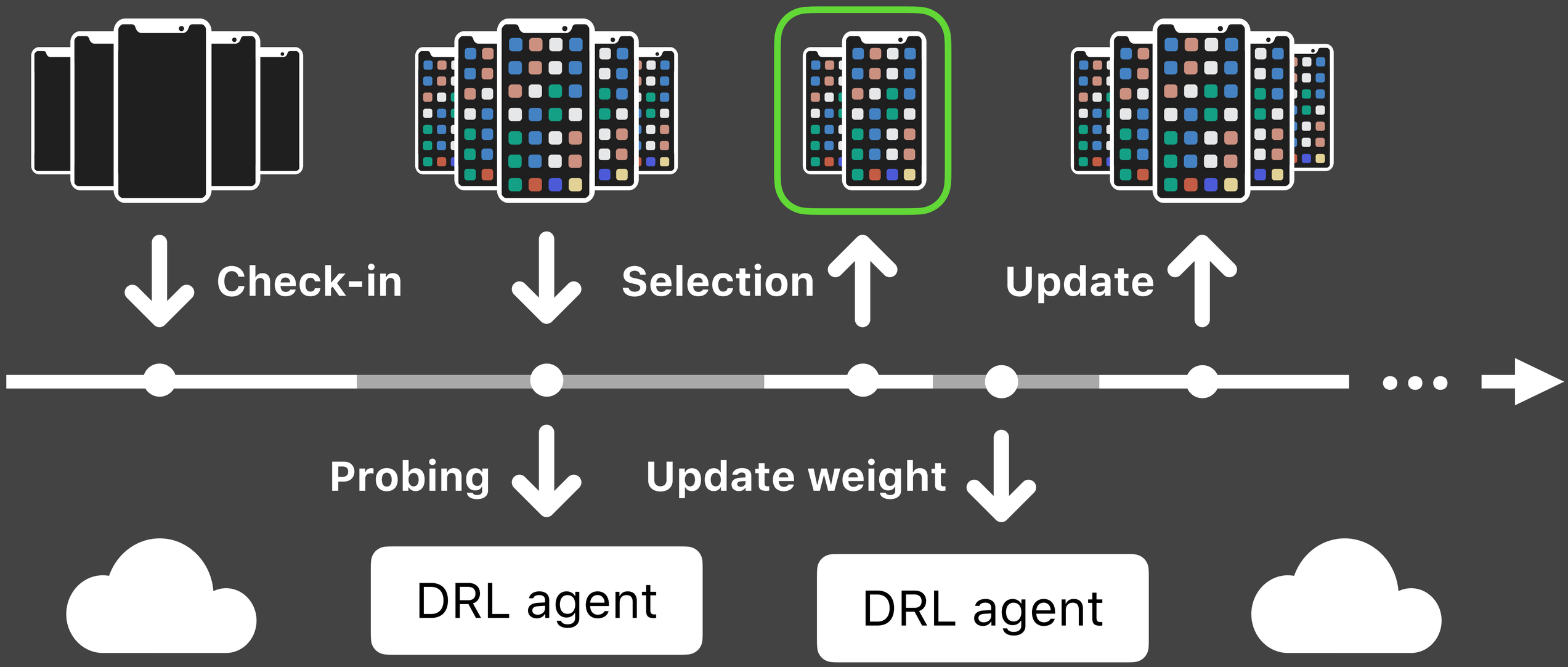
$$\textbf{Max} \quad R = \sum_{t=1}^{T} \gamma^{t-1} r_t = \sum_{t=1}^{T} \gamma^{t-1} (\Xi^{(\omega_t - \Omega)} - 1)$$

discount factor

$\gamma \in (0,1)$


Reward r_t
Agent
DDQN
Features
softmax
$\mathbf{a}_t$
Action
Environment
FL server
State $\mathbf{s}_{t-1}$


Cumulative Discounted Reward
0
-28
-55
-83
-110
1
11
21
31
41
51
61
71
81
91
101
111
121
131
141
151
161
171
Episode
Training the DRL agent

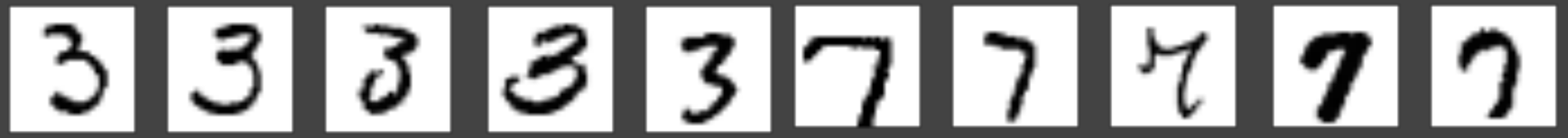

Check-in
Selection
Update
Probing
Update weight
DRL agent
DRL agent

Evaluating Our Solution

Benchmark: MNIST, FashionMNIST, CIFAR-10

Non-IID level: 1, half-and-half, 80%, 50%

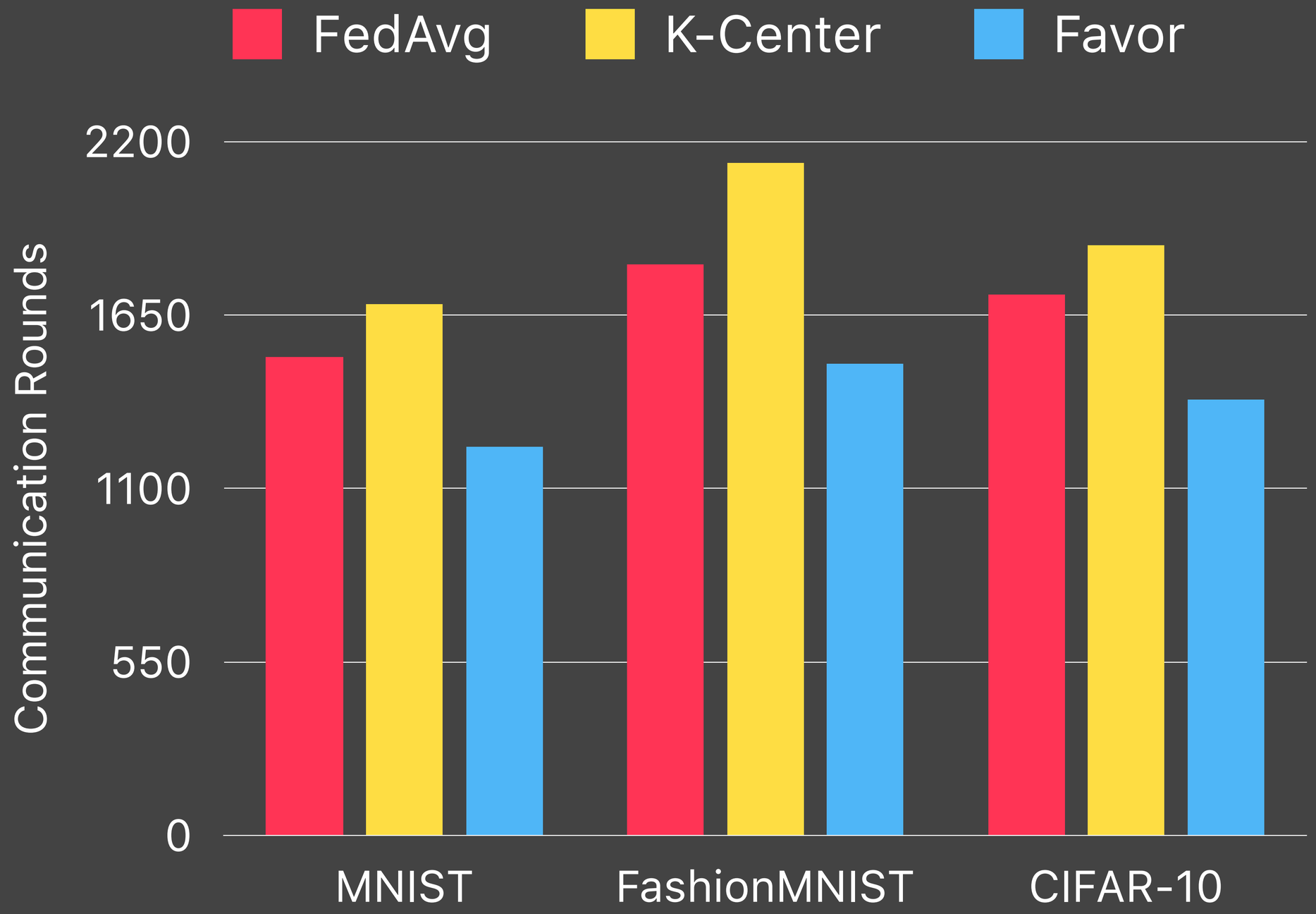
Half-and-half



80%

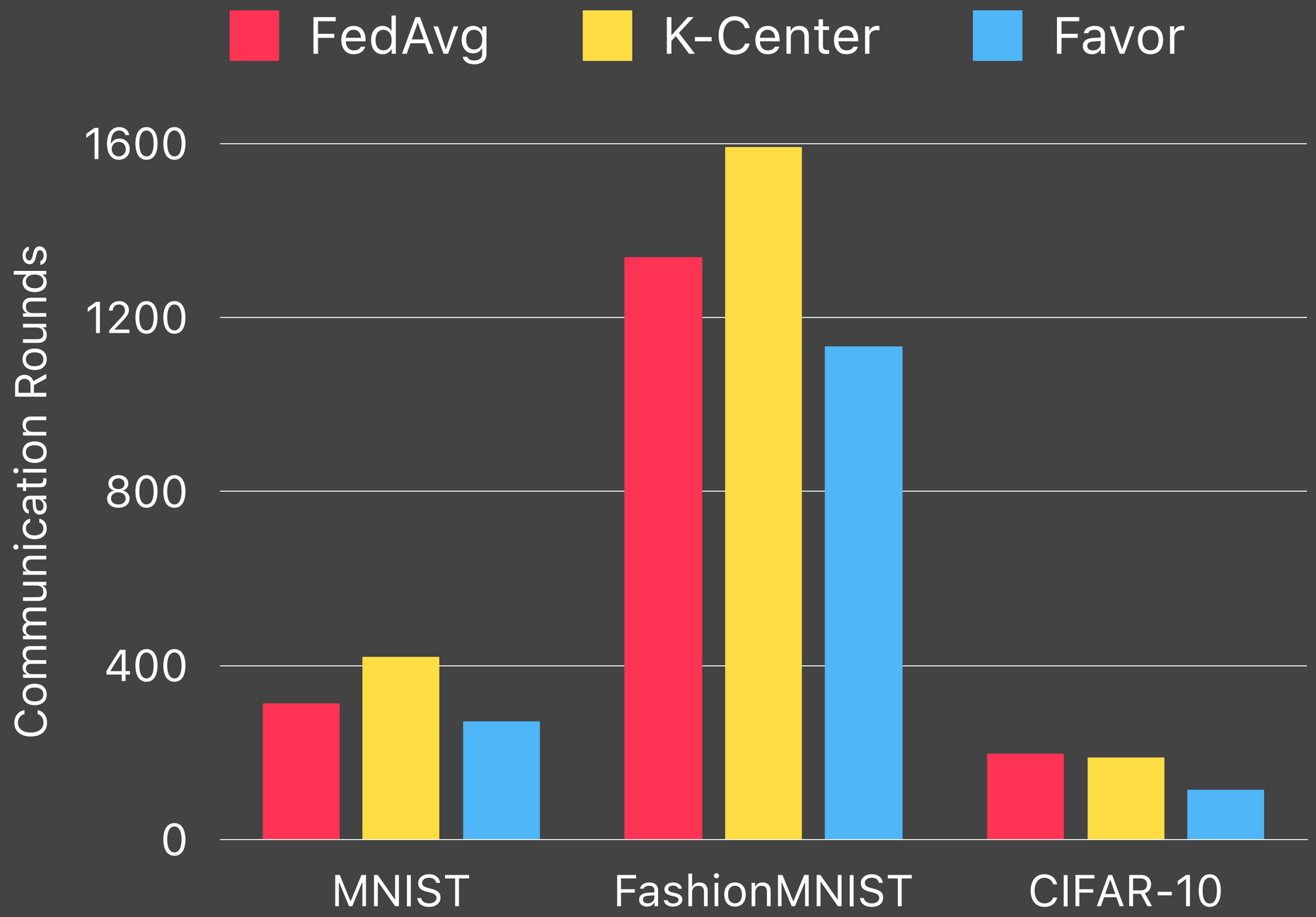
Non-IID level

1



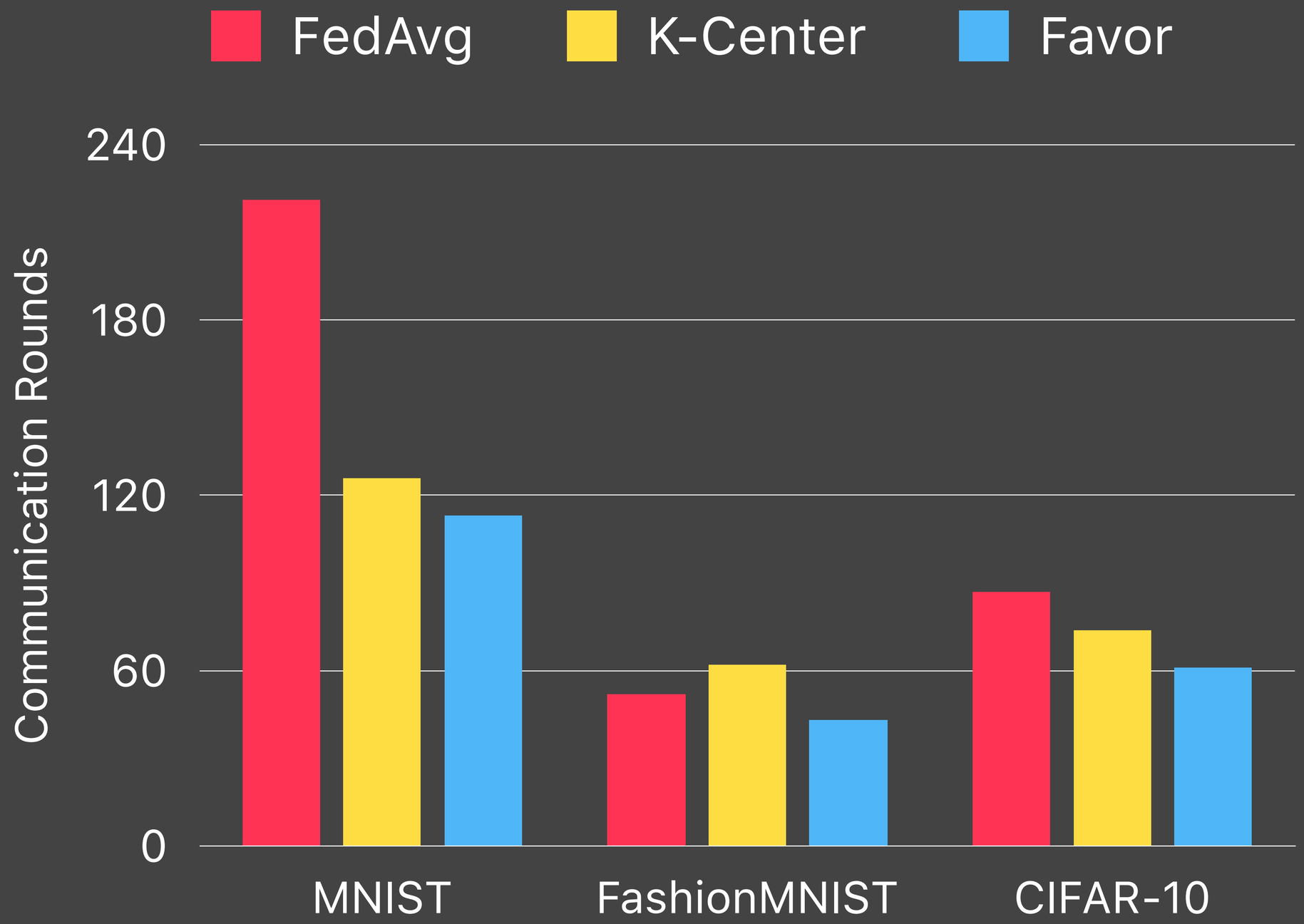
Non-IID level

half & half



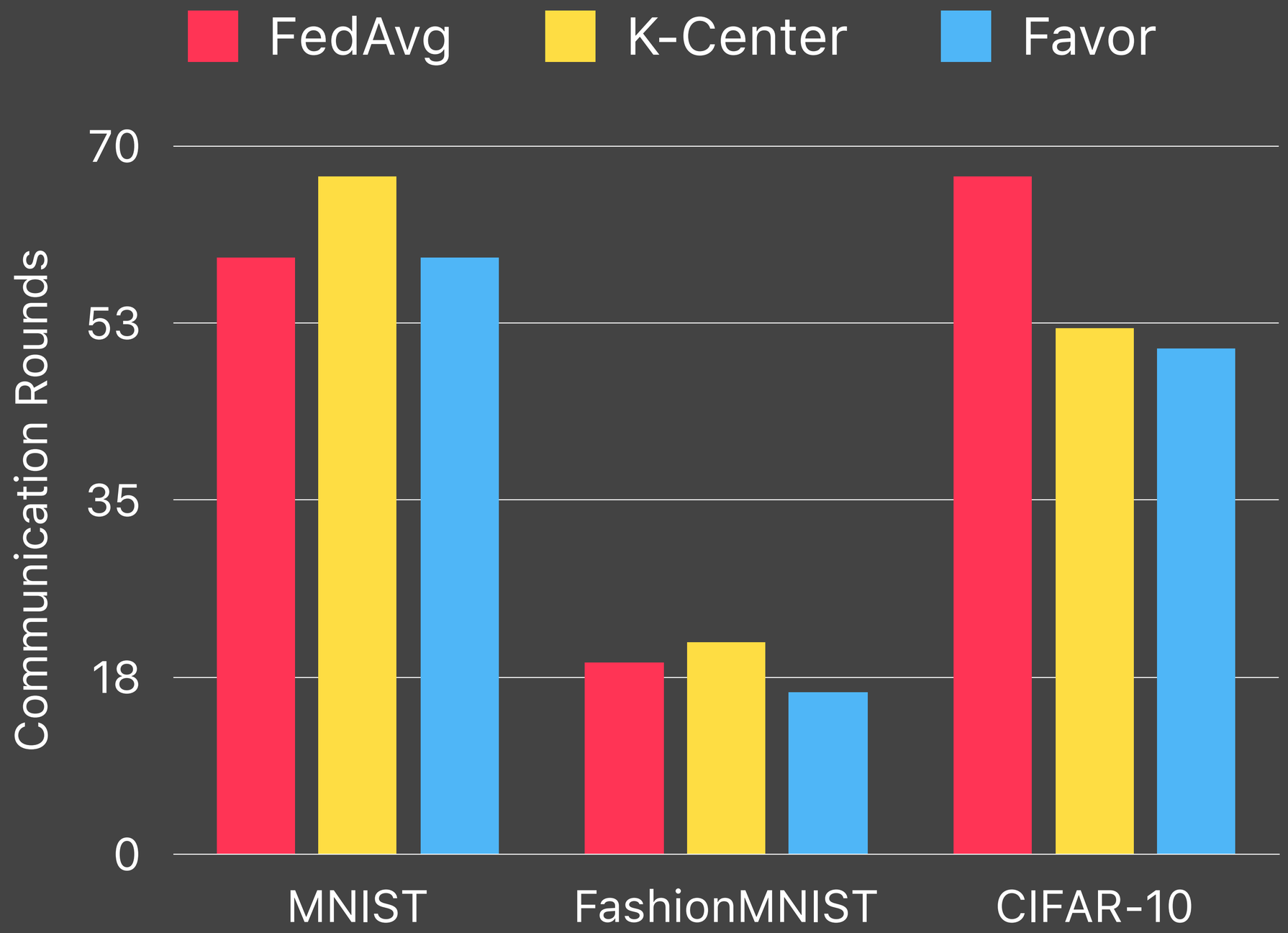
Non-IID level

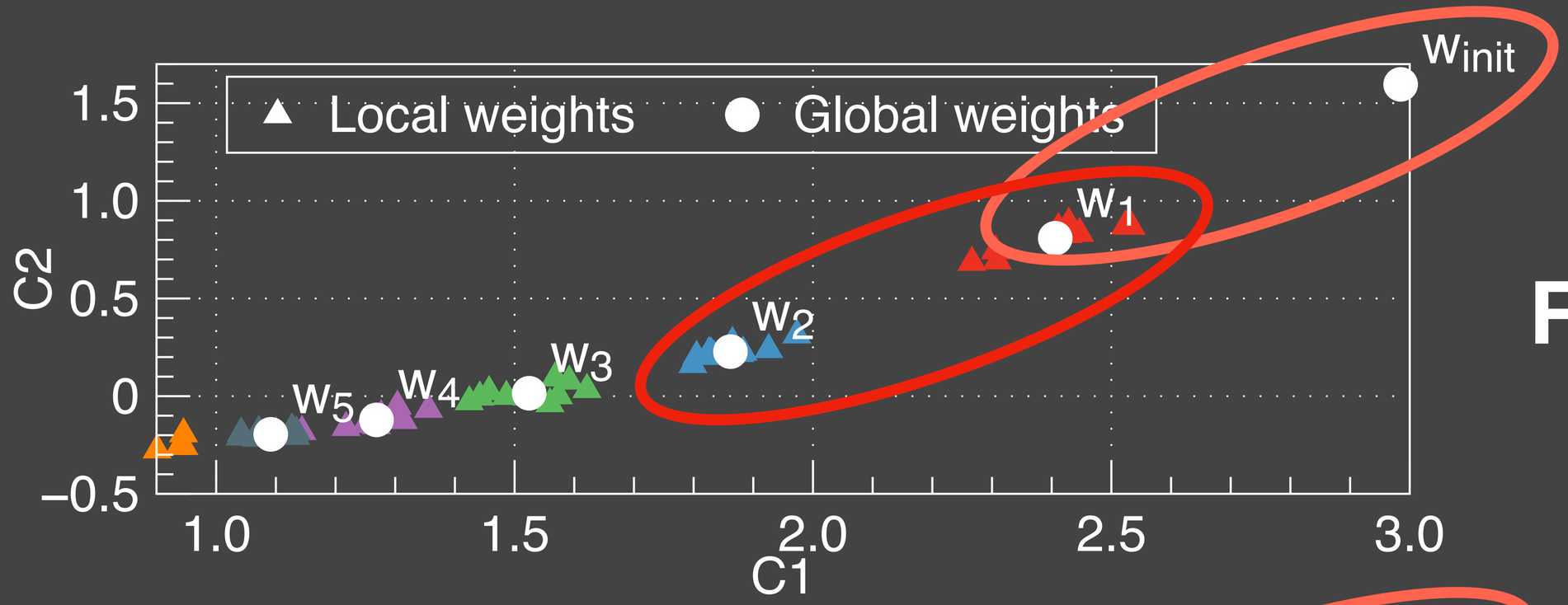
80%



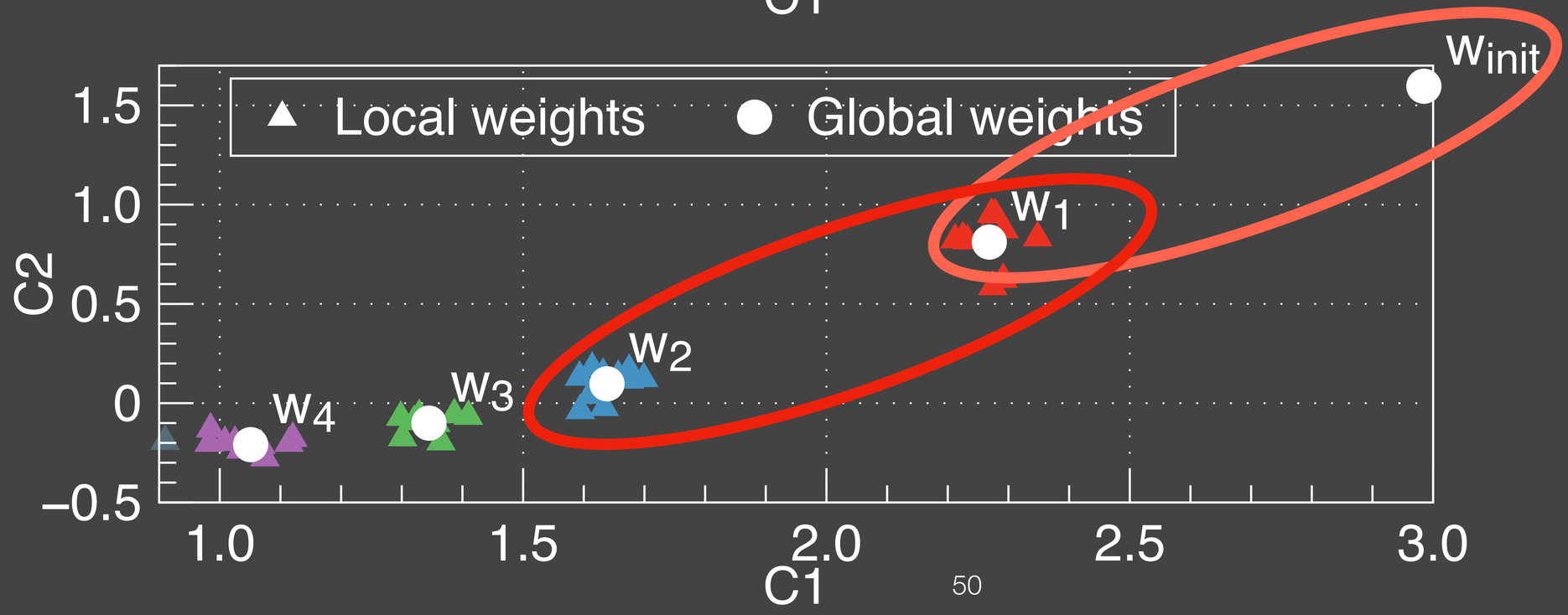
Non-IID level

50%





FedAvg



Favor

Indirect data distribution probing

DRL-based device selection

Communication rounds can be reduced by up to

- **49% on the MNIST**
- **23% on FashionMNIST**
- **42% on CIFAR-10**