# `pfl-research`: simulation framework for accelerating research in Private Federated Learning

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github.com/apple/pfl-research

# Problems with learning from consumer devices data

Central data curation concerns

- Privacy
- Regulations
- Bandwidth

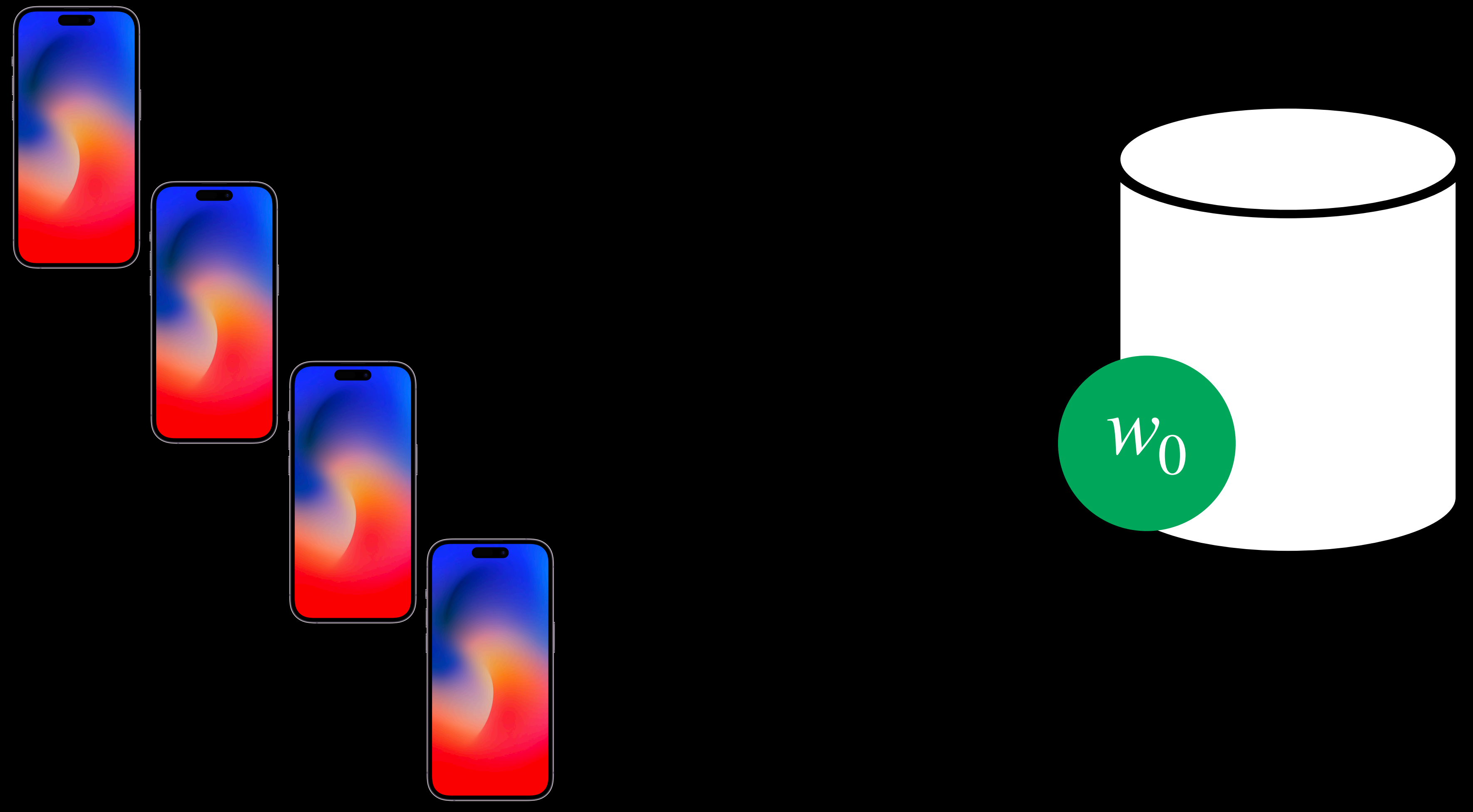
We want to learn from real user generated data on the edge

- Magnitudes more data available because of above
- Same distribution as during inference

# Federated Learning

Train ML models without uploading the datasets to a central server

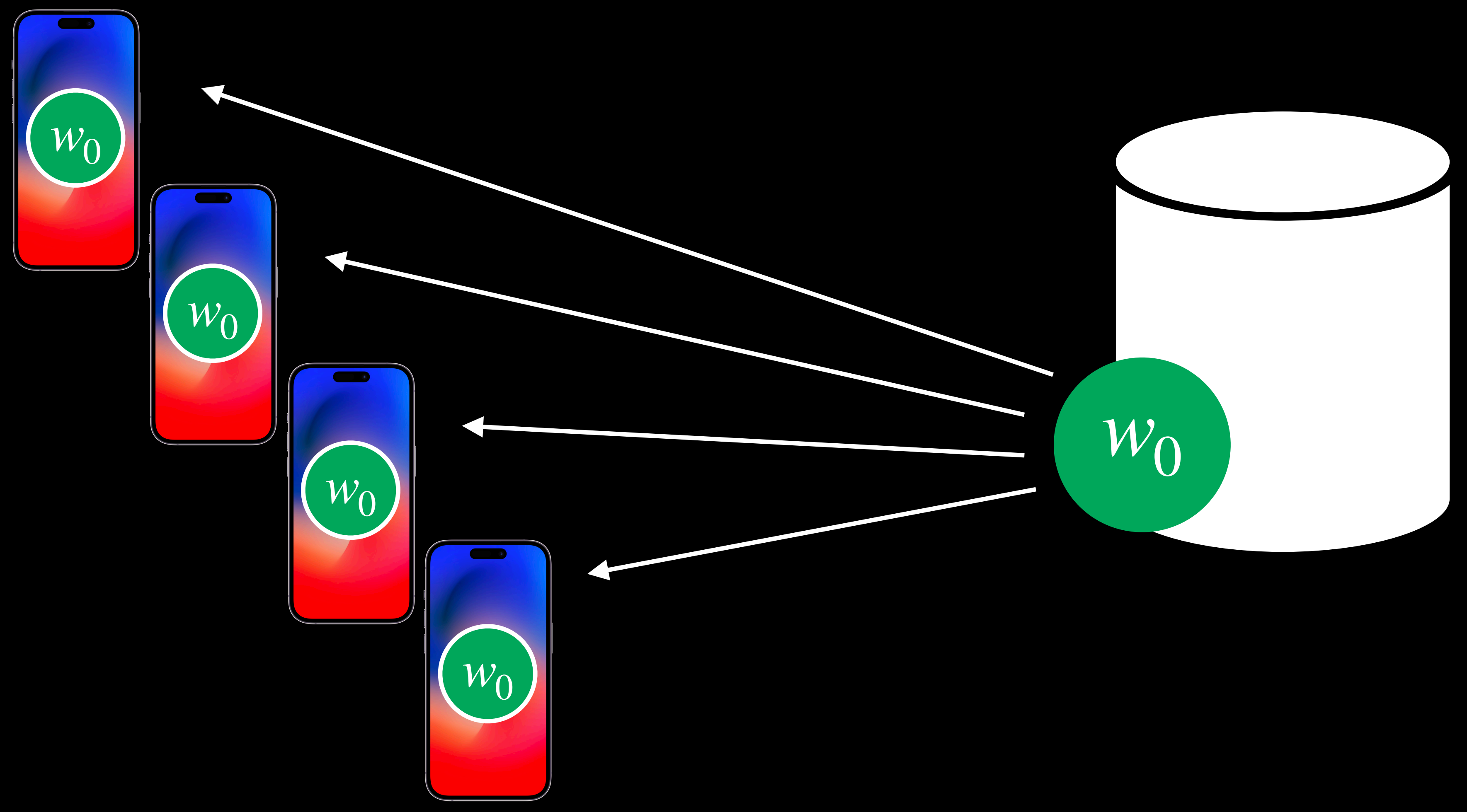
# Federated Learning




Initial global model is held server-side

1. Initialize $w_0$
2. **for** $t = 0, \ldots, T-1$ **do**
3. $\quad S \leftarrow$ (Random subset of $n$ clients)
4. $\quad$ **for** each client $k \in S$ with dataset $D_k$ in parallel **do**
5. $\quad\quad$ **for** each local iteration $i$ **do**
6. $\quad\quad\quad w^k_{t+1} \leftarrow w^k_{t+1} - \eta \mathscr{L}(w^k_{t+1}; D_k)$
7. $\quad\quad \Delta_k = w^k_{t+1} - w_t$
8. $\quad w_{t+1} \leftarrow w_t + \dfrac{1}{|S|} \sum_{k=1}^{|S|} \Delta_k$

# Federated Learning




The global model is distributed to devices

1. Initialize $w_0$
2. **for** $t = 0, \ldots, T-1$ **do**
3. $S \leftarrow$ (Random subset of $n$ clients)
4. **for** each client $k \in S$ with dataset $D_k$ in parallel **do**
5. **for** each local iteration $i$ **do**
6. $w_{t+1}^k \leftarrow w_{t+1}^k - \eta \mathscr{L}(w_{t+1}^k; D_k)$
7. $\Delta_k = w_{t+1}^k - w_t$
8. $w_{t+1} \leftarrow w_t + \frac{1}{|S|} \sum_{k=1}^{|S|} \Delta_k$

# Federated Learning


Devices compute local model updates from user data

1. Initialize $w_0$
2. **for** $t = 0, \ldots, T-1$ **do**
3. $S \leftarrow$ (Random subset of $n$ clients)
4. for each client $k \in S$ with dataset $D_k$ in parallel **do**
5. **for** each local iteration $i$ **do**
6. $w_{t+1}^k \leftarrow w_{t+1}^k - \eta \mathscr{L}(w_{t+1}^k; D_k)$
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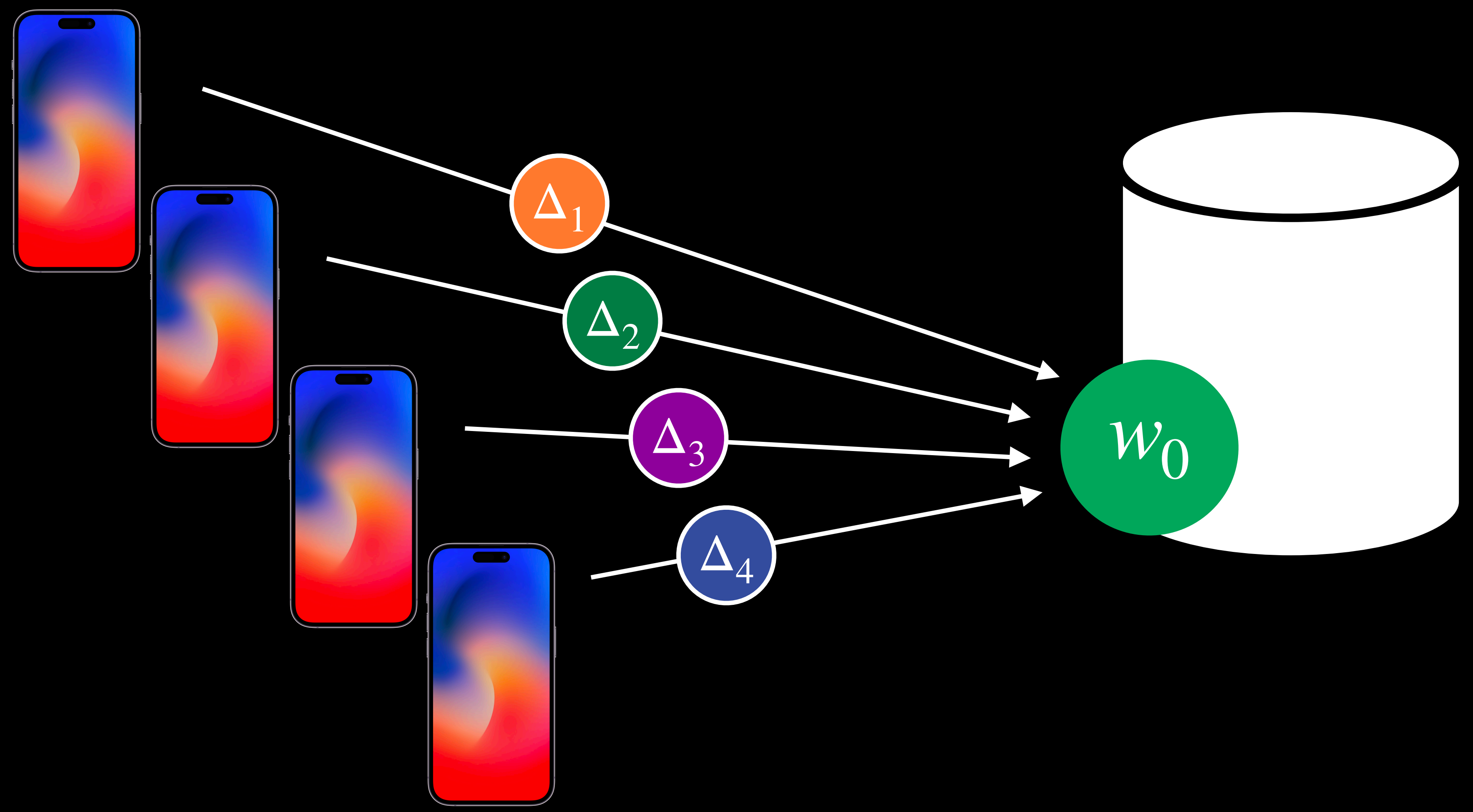
# Federated Learning




Devices report model updates

1. Initialize $w_0$
2. **for** $t = 0,\ldots,T-1$ **do**
3. $S \leftarrow$ (Random subset of $n$ clients)
4. for each client $k \in S$ with dataset $D_k$ in parallel **do**
5. for each local iteration $i$ **do**
6. $w_{t+1}^k \leftarrow w_{t+1}^k - \eta \mathscr{L}(w_{t+1}^k; D_k)$
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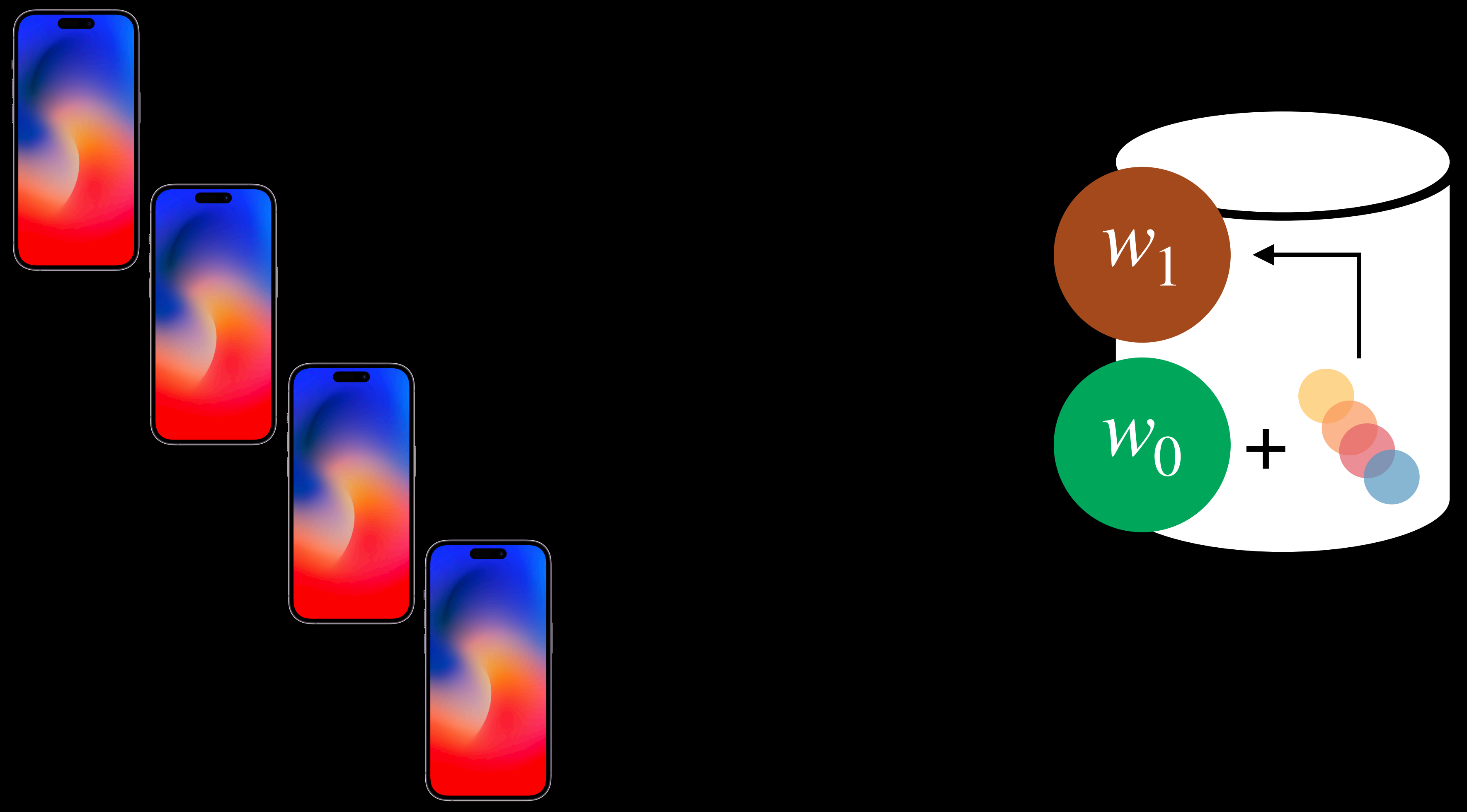
# Federated Learning




Central model is updated with aggregated updates

1. Initialize $w_0$
2. **for** $t = 0,\ldots,T-1$ **do**
3. $S \leftarrow$ (Random subset of $n$ clients)
4. for each client $k \in S$ with dataset $D_k$ in parallel **do**
5. for each local iteration $i$ **do**
6. $w_{t+1}^k \leftarrow w_{t+1}^k - \eta \mathscr{L}(w_{t+1}^k; D_k)$
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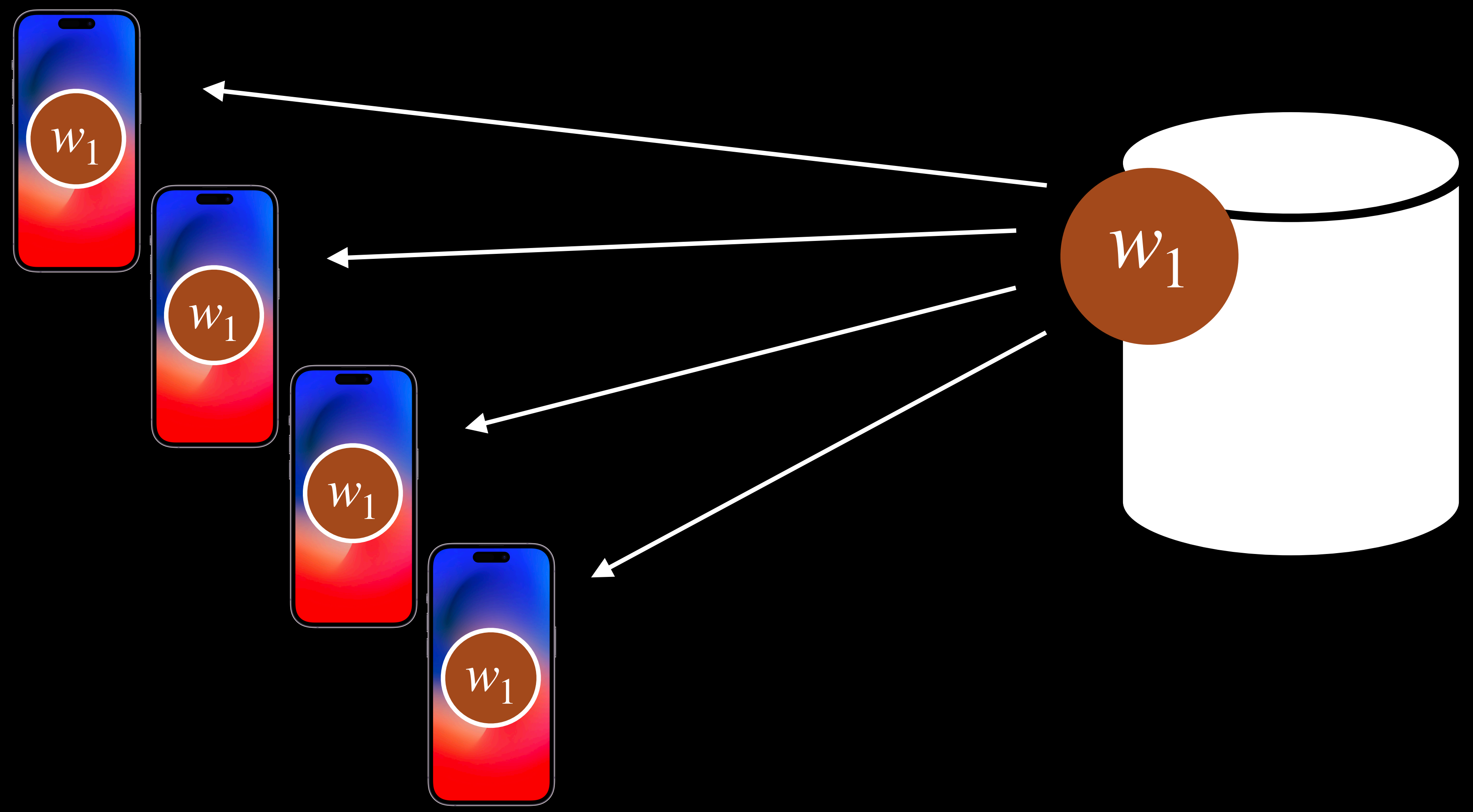
# Federated Learning




New model is distributed to devices

1. Initialize $w_0$
2. **for** $t = 0,\ldots,T-1$ **do**
3. $\quad S \leftarrow$ (Random subset of $n$ clients)
4. $\quad$ for each client $k \in S$ with dataset $D_k$ in parallel **do**
5. $\qquad$ for each local iteration $i$ **do**
6. $\qquad\quad w_{t+1}^k \leftarrow w_{t+1}^k - \eta\mathscr{L}(w_{t+1}^k; D_k)$
7. $\qquad \Delta_k = w_{t+1}^k - w_t$
8. $\quad w_{t+1} \leftarrow w_t + \frac{1}{|S|}\sum_{k=1}^{|S|}\Delta_k$

# pfl-research

Simulation framework for accelerating research in PFL

github.com/apple/pfl-research

https://github.com/apple/pfl-research

# Contributions to open-source

`pip install pfl`

# Why pfl-research

- Better flexibility, expressiveness and modularity than alternatives.
- Fastest scalable simulations for large experiments.
- Supports PyTorch, TF and MLX, we unify benchmarks across frameworks.
- Supports other models in addition to neural networks, e.g. GBDTs, GMMs.
- Support for SoTA open-source privacy accountants & mechanisms
- Simple to understand

# pfl-research - example code

```python
torch_model = torch.nn.Sequential([torch.nn.Linear(4,1)])
model = PyTorchModel(torch_model, ...)

sampler = lambda: user_ids[np.random.randint(0, len(user_ids))]
userid_to_data: Dict[int, Tuple[torch.Tensor, torch.Tensor]]
train_feddata = FederatedDataset.from_slices(userid_to_data, sampler)

dp_accountant = PRVPrivacyAccountant(epsilon=2, delta=1e-6, ...)
dp_mechanism = GaussianMechanism.from_privacy_accountant(accountant=dp_accountant, clipping_bound=1.0))

backend = SimulatedBackend(training_data=train_feddata, postprocessors=[dp_mechanism], ...)

algorithm = FederatedAveraging()
algorithm.run(
    backend=backend,
    model=model,
    algorithm_params=NNAlgorithmParams(...),
    model_train_params=NNTrainHyperParams(...),
    model_eval_params=NNEvalHyperParams(...))

```

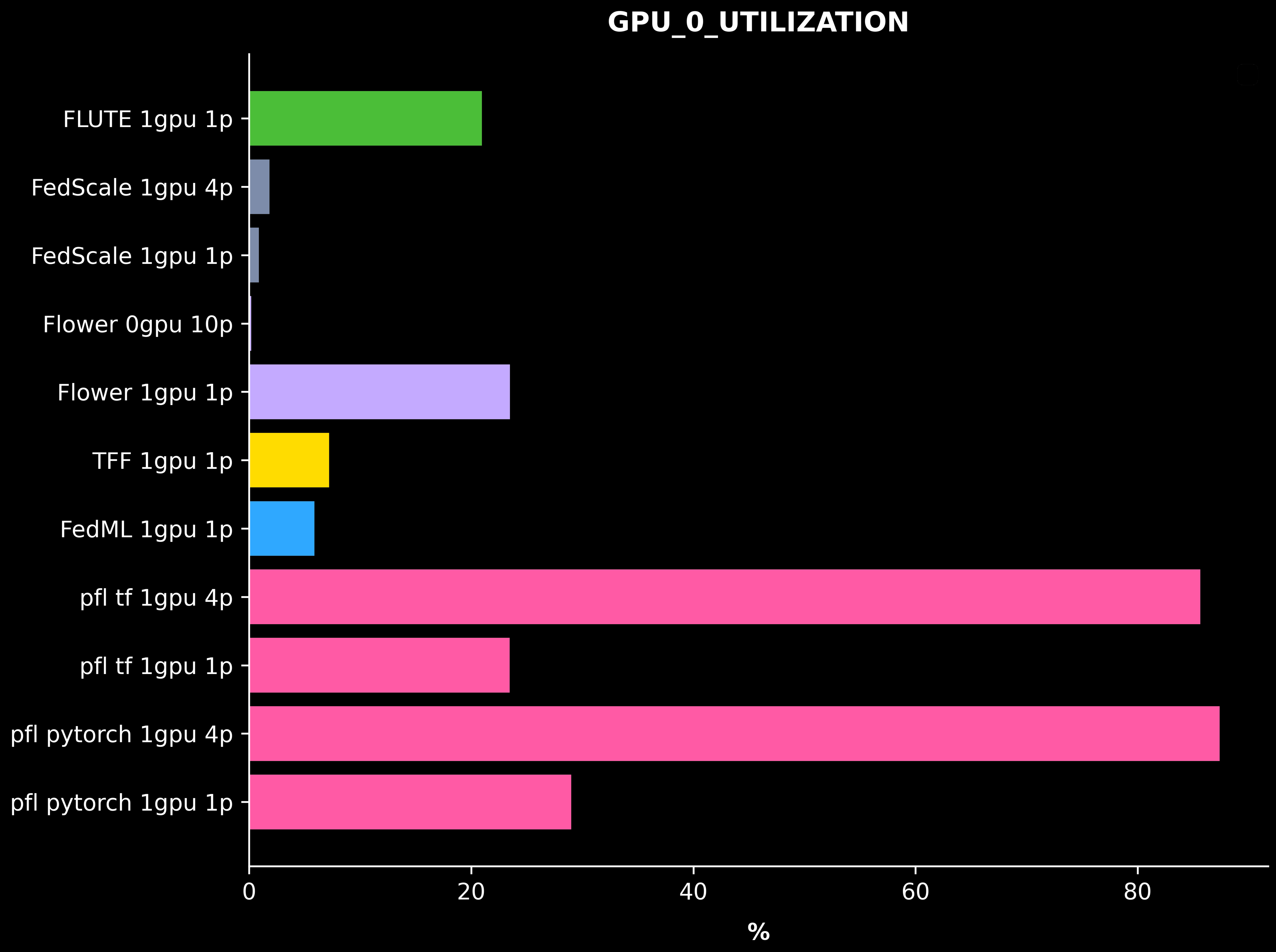
# Competitive Analysis

Benchmarking against open-source alternatives, 1GPU

| Dataset | FL Framework | #processes | NN Framework | Time to converge (min) | pfl is faster factor |
|---|---|---|---|---|---|
| CIFAR10 | pfl-research | 1 | PyTorch | 10.13 | |
| | | 5 | PyTorch | 4.2 | 1x |
| | | 1 | TF2 | 15.3 | |
| | | 5 | TF2 | 7.9 | |
| | FedML | 1 | PyTorch | 91 | 22x |
| | TFF (Google) | 10 | TF2 | 82 | 20x |
| | Flower (Oxford/Cambridge) | 1 | PyTorch | 87 | 16x |
| | | 10 | PyTorch | 29 | 7x |
| | FedScale | 1 | PyTorch | 425 | 101x |
| | | 4 | PyTorch | 302 | 72x |
| | FLUTE (Microsoft) | 1 | TF2 | 68 | 16x |

Numbers are from the date of release of pfl 0.1.0

# Competitive analysis

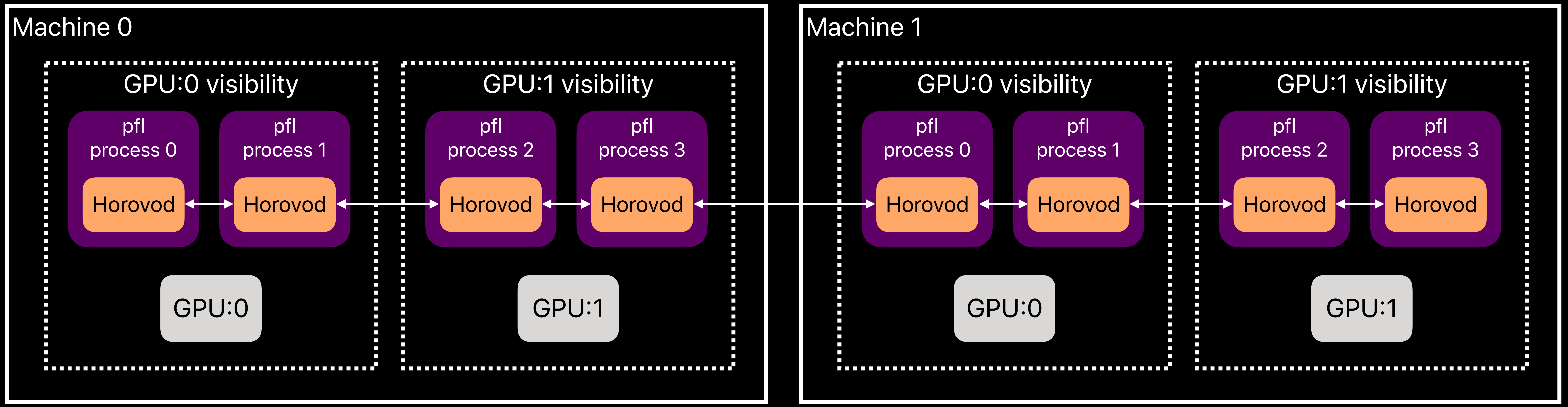


# pfl-research - distributed simulations

Multi-process, multi-GPU, multi-machine

## Communication overhead

- All-reduce gradients + metrics



# Competitive Analysis

Benchmarking against open-source alternatives

| Dataset | FL Framework | GPUs | #processes per GPU | NN Framework | Time to converge (h) | pfl is faster factor |
|---|---|---|---|---|---|---|
| FLAIR | **pfl-research 0.1.0** | **4** | **2** | PyTorch | 2.16 | |
| | **pfl-research 0.2.0** | **4** | **2** | PyTorch | 1.77 | 1x |
| | **TFF (Google)** | **4** | **5** | TF2 | 18 | 10x |
| | **Flower** | **4** | **5** | PyTorch | 28.8 | 16x |

Numbers are from the date of release of pfl 0.1.0

# Official benchmarks

| | | | | | | |
|---|---|---|---|---|---|---|
| CIFAR10<br>StackOverflow<br>FLAIR<br>HuggingFace LLM FT | X | IID<br>non-IID | X | No DP<br>Central DP | X | TF<br>PyTorch<br>MLX |

* May still be work in progress at the time of this presentation

# Benchmarking pfl-research with MLX on Apple silicon

| Dataset | Hardware | #processes | NN Framework | Time to converge (min) | A100 is faster factor |
|---|---|---|---|---|---|
| CIFAR10 | 1x Nvidia A100 GPU | 1 | PyTorch | 10.13 | |
| | | 5 | PyTorch | 4.2 | |
| | | 1 | TF2 | 15.3 | |
| | | 5 | TF2 | 7.9 | |
| | M1 Pro | 1 | MLX | 21.7 | 5.2x |
| | | 4 | | 15.2 | 3.6x |
| | M3 Max | 1 | | 10.2 | 2.4x |
| | | 5 | | 5.3 | 1.3x |

Numbers are from the date of release of pfl 0.1.0

# Benchmarking pfl-research with MLX on Apple silicon

| Dataset | Hardware | #processes | NN Framework | Time to converge | A100 is faster factor |
|---|---|---|---|---|---|
| StackOverflow | **4x** Nvidia A100 GPU | 5 | PyTorch | 52m | |
| | M1 Pro | 5 | MLX | 8h 12m | 9.4x |
| | M3 Max | 5 | | 3h 6m | 3.6x |

Numbers are from the date of release of pfl 0.1.0

# Getting started

Tutorials

github.com/apple/pfl-research/tree/main/tutorials

Documentation

apple.github.io/pfl-research

Benchmarks

github.com/apple/pfl-research/tree/main/benchmarks