

FedScale

Benchmarking Model and System Performance of Federated Learning

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Harsha V. Madhyastha, Mosharaf Chowdhury

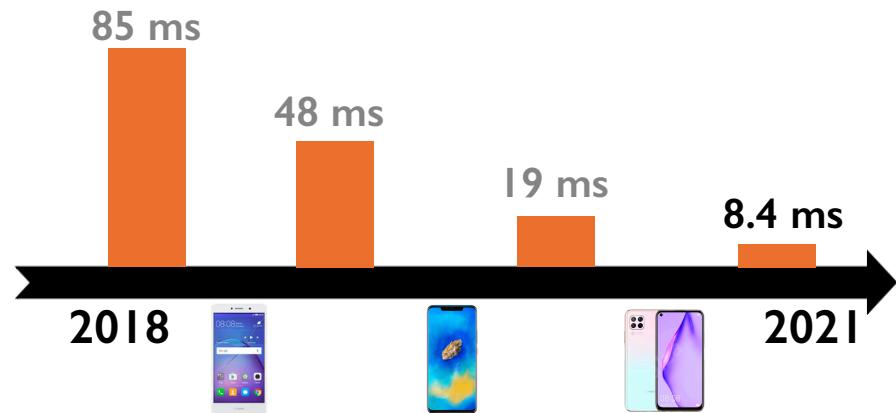


Emerging Trend of Machine Learning

Edge devices generate massive data



Model compute latency becomes smaller

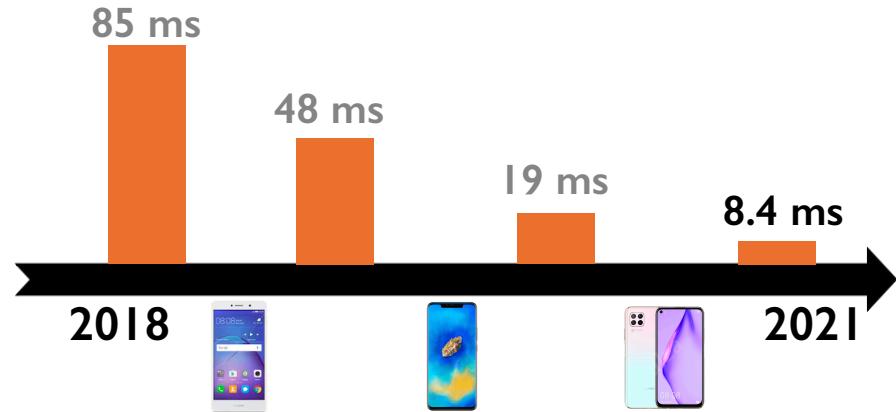


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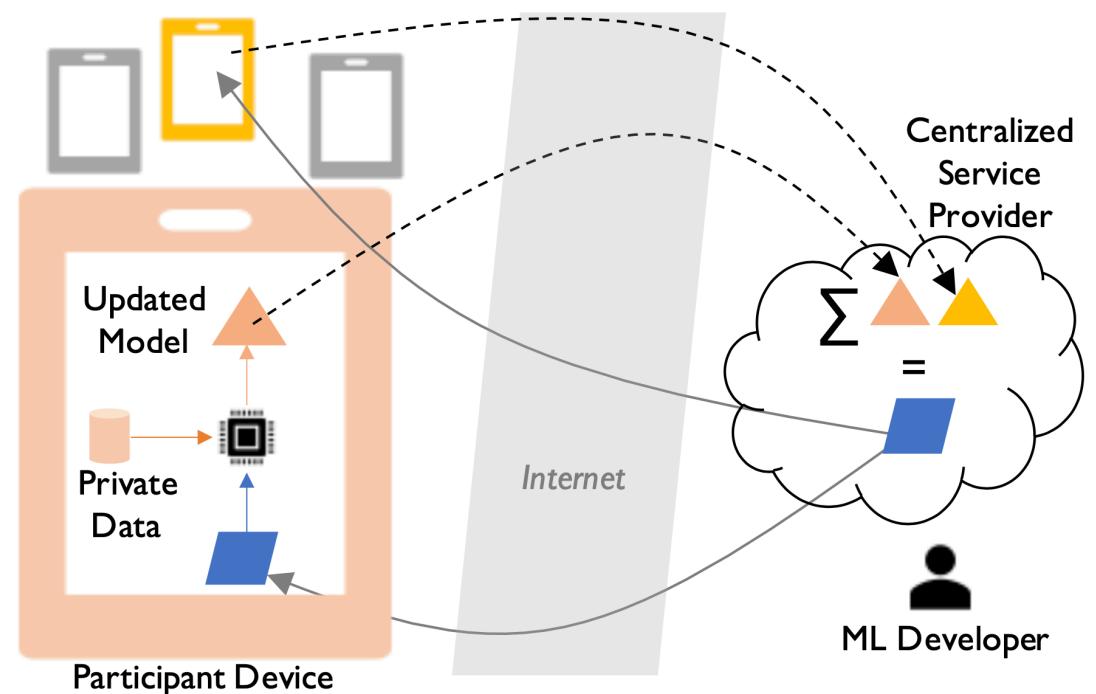


Model compute latency becomes smaller



Federated learning helps

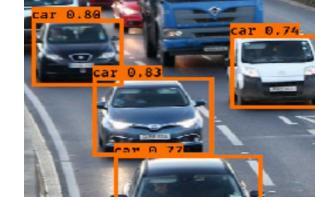
- Reduce data migration/privacy risk
- Learn on fresh real-world data
- ...



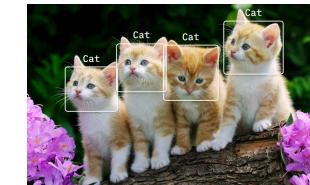
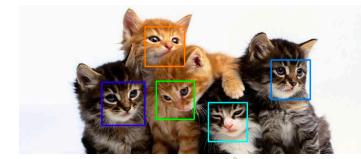
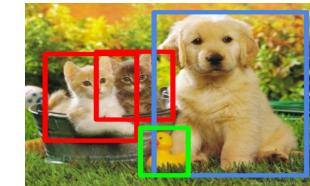
Challenges in Federated Learning (FL)

	FL	In-cluster ML
Data	Heter.	Homogeneous via shuffling

Client A



Client B



Heterogeneous data distribution

Challenges in Federated Learning (FL)

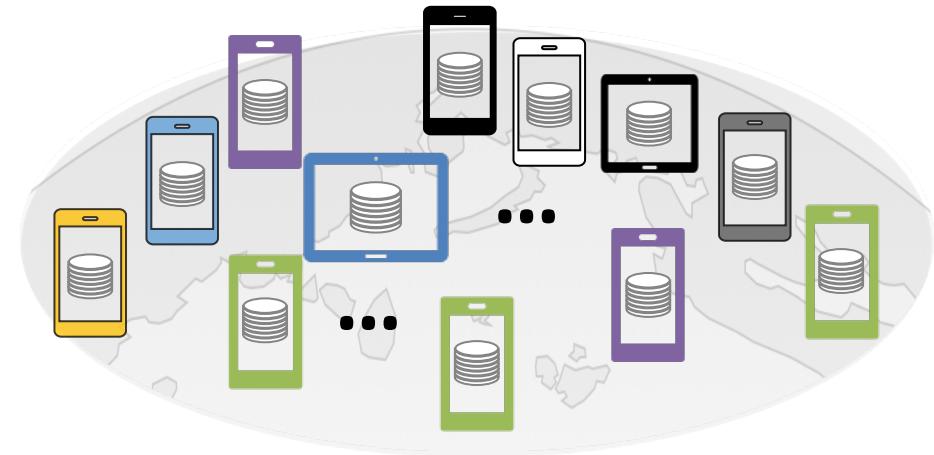
	FL	In-cluster ML
Data	Heter.	Homogeneous via shuffling
System	Heter.	Homogeneous



Heterogeneous system speed

Challenges in Federated Learning (FL)

	FL	In-cluster ML
Data	Heter.	Homogeneous via shuffling
System	Heter.	Homogeneous
Scale	$O(1M)$	$O(10)$
Dynamics	Client can drop out/rejoin	Negligible
...



Large scale and dynamics

While Existing FL Optimizations Are Diverse ...

- To tackle challenges, we optimize
 - Statistical efficiency
 - Round-to-accuracy convergence
 - Final model accuracy, ...
 - System efficiency
 - Reduce network traffics
 - Discard system stragglers, ...
 - Privacy and security
 - ...

Mistify: Automating DNN Model Porting for On-Device Inference at the Edge

TOWARDS FEDERATED LEARNING AT SCALE: SYSTEM DESIGN

APPLIED FEDERATED LEARNING:
IMPROVING GOOGLE KEYBOARD QUERY SUGGESTIONS

Oort: Efficient Federated Learning via Guided Participant Selection

An Efficient Framework for
Clustered Federated Learning

An Efficient Framework for
Clustered Federated Learning

Diverse FL efforts in algorithm/system

Inefficiency of Existing FL Benchmarks

	LEAF	FedEval	FedML	Flower
Heter. Client Dataset	○	✗	○	○
Realistic Datasets	✗	✗	✗	✗

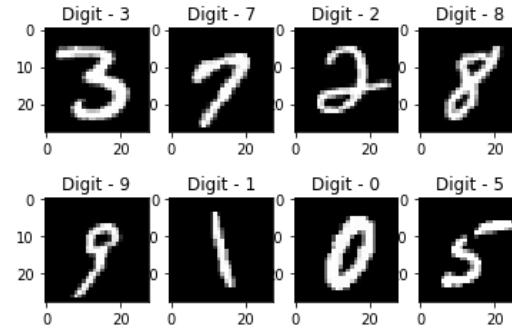
Few **realistic** datasets

○: limited support

Inefficiency of Existing FL Benchmarks

	LEAF	FedEval	FedML	Flower
Heter. Client Dataset	○	✗	○	○

Few **realistic** datasets



Traditional datasets are not representative

○: limited support

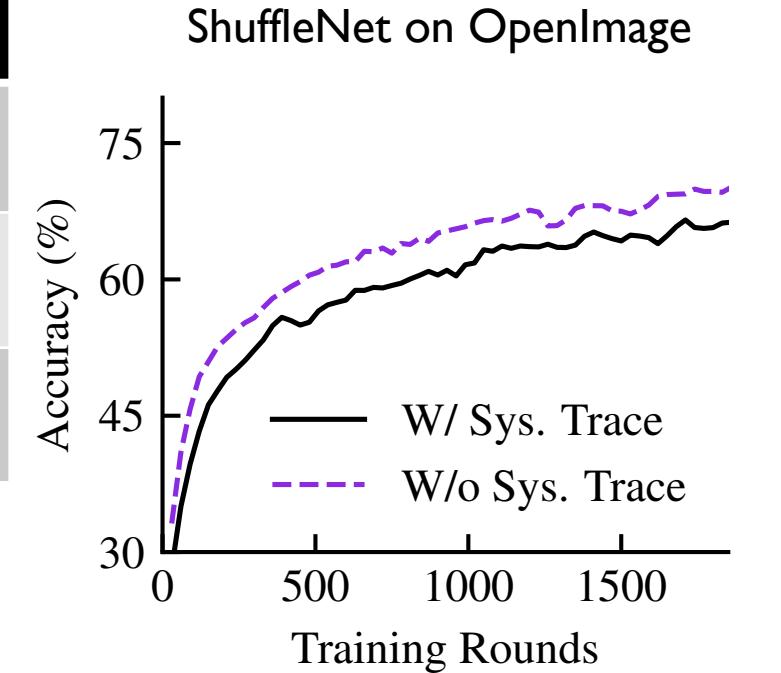
Inefficiency of Existing FL Benchmarks

	LEAF	FedEval	FedML	Flower
Heter. Client Dataset	○	✗	○	○
Heter. System Speed	✗	✗	✗	✗
Client Availability	✗	✗	✗	✗

○: limited support

Inefficiency of Existing FL Benchmarks

	LEAF	FedEval	FedML	Flower
Heter. Client Dataset	○	✗	○	○
Heter. System Speed	✗	✗	✗	✗
Client Availability	✗	✗	✗	✗



Overlooking system aspects leads to **optimistic** performance

○: limited support

Inefficiency of Existing FL Benchmarks

	LEAF	FedEval	FedML	Flower
Heter. Client Dataset	○	✗	○	○
Heter. System Speed	✗	✗	✗	✗
Client Availability	✗	✗	✗	✗
Scalable Platform	✗	○	○	✓

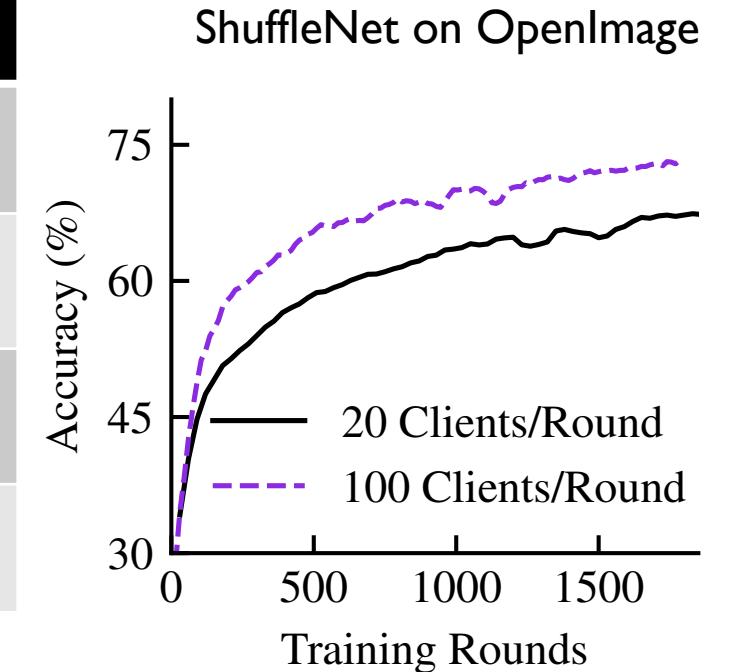
Suboptimal scalability in distributed setting

○: limited support

Inefficiency of Existing FL Benchmarks

	LEAF	FedEval	FedML	Flower
Heter. Client Dataset	○	✗	○	○
Heter. System Speed	✗	✗	✗	✗
Client Availability	✗	✗	✗	✗
Scalable Platform	✗	○	○	✓

Suboptimal scalability in distributed setting



Inability for large-scale evaluation
under-reports FL performance

○: limited support

Inefficiency of Existing FL Benchmarks

	LEAF	FedEval	FedML	Flower
Heter. Client Dataset	○	✗	○	○
Heter. System Speed	✗	✗	✗	✗
Client Availability	✗	✗	✗	✗
Scalable Platform	✗	○	○	✓
Real FL Runtime	✗	✗	✗	✗
Flexible APIs	✗	✗	✓	✓

○: limited support

Missing FL runtime
discourages system
optimizations

Inefficiency of Existing FL Benchmarks

	LEAF	FedEval	FedML	Flower	FedScale
Heter. Client Dataset	○	✗	○	○	✓
Heter. System Speed	✗	✗	✗	✗	✓
Client Availability	✗	✗	✗	✗	✓
Scalable Platform	✗	○	○	✓	✓
Real FL Runtime	✗	✗	✗	✗	✓
Flexible APIs	✗	✗	✓	✓	✓

○: limited support

fedscale.ai

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Realistic FL
Datasets

2

Scalable Eval
Platform

3

Easy
Development

Statistical Client Datasets

- ~20 diverse datasets w/ realistic partition
 - CV, NLP, RL tasks
 - Small/Medium/Large scales
 - Standardized data loader

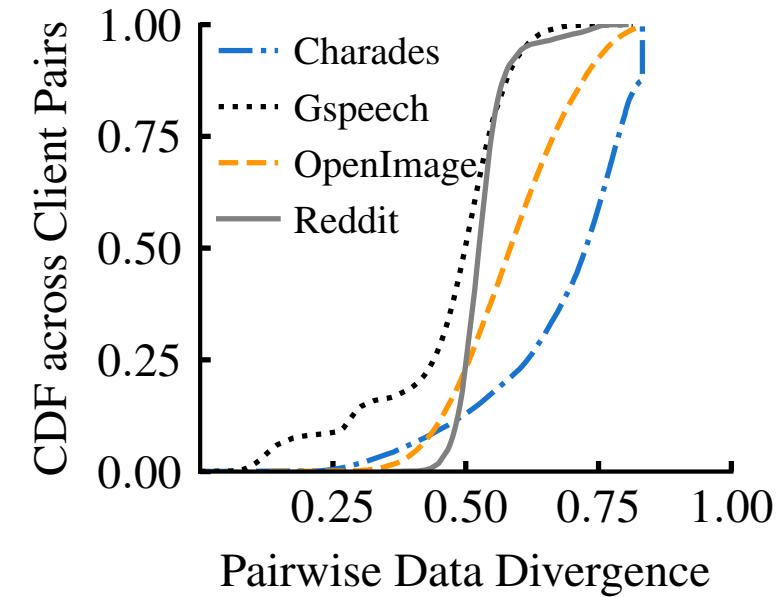
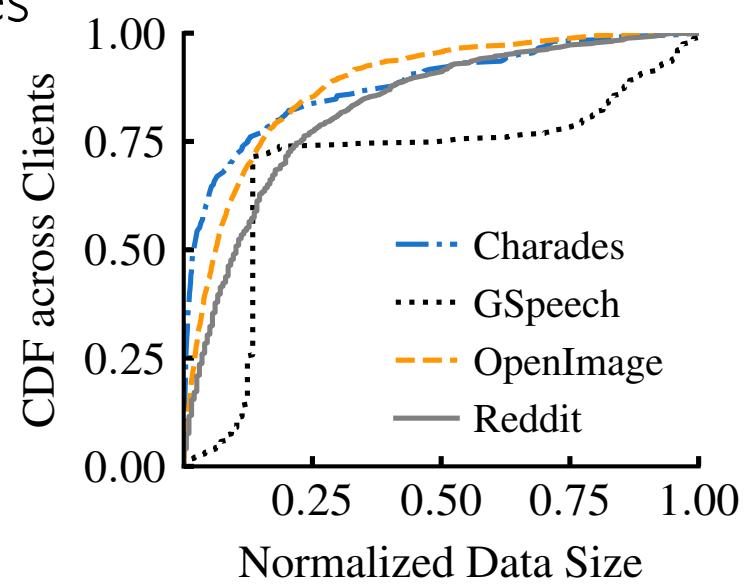
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CV	iNature	Image	2,295	193K
	FEMNIST	Image	3,400	640K
	OpenImage	Image	13,771	1.3M
	Google Landmark	Image	43,484	3.6M
	Charades	Video	266	10K
	VLOG	Video	4,900	9.6K
	Waymo Motion	Video	496,358	32.5M
NLP	Europarl	Text	27,835	1.2M
	Blog Corpus	Text	19,320	137M
	Stackoverflow	Text	342,477	135M
	Reddit	Text	1,660,820	351M
	Amazon Review	Text	1,822,925	166M
	CoQA	Text	7,189	114K
	LibriTTS	Text	2,456	37K
	Google Speech	Audio	2,618	105K
	Common Voice	Audio	12,976	1.1M
Misc ML	Taobao	Text	182,806	20.9M
	Fox Go	Text	150,333	4.9M

Some FedScale Datasets

Statistical Client Datasets

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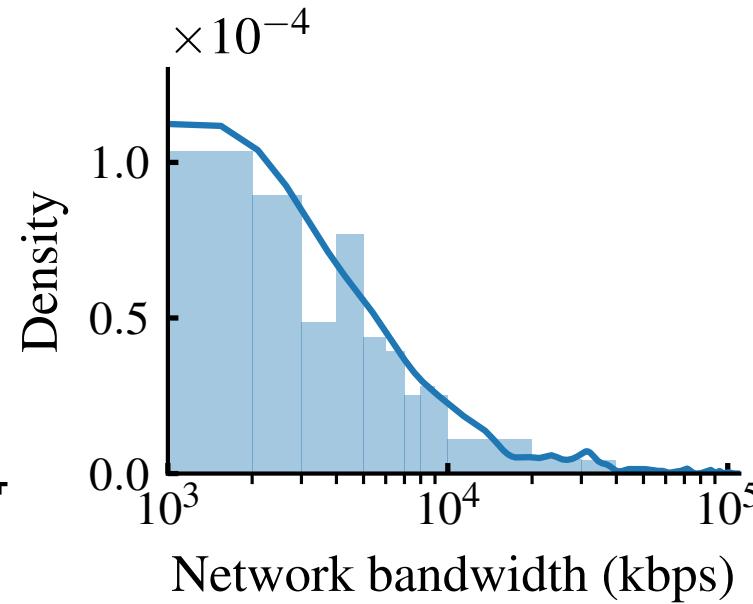
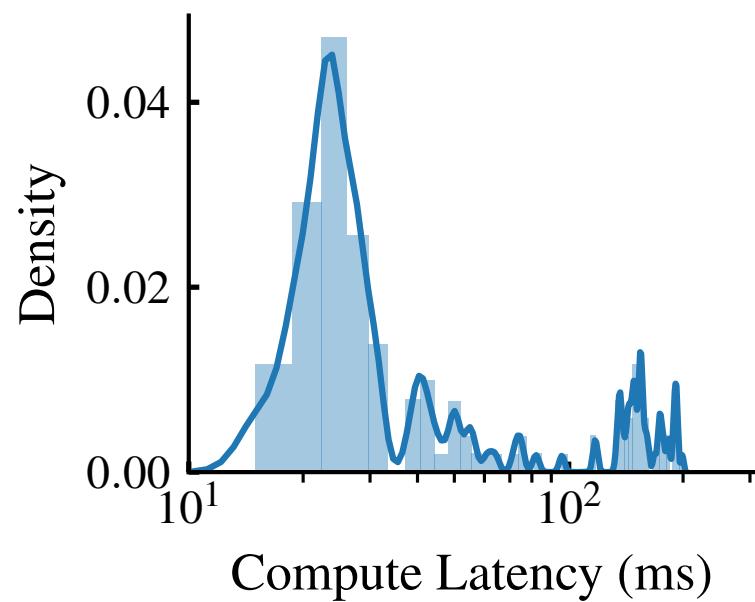
Realistic client data is heterogeneous in size and distribution

Statistical Client Datasets

- ~20 diverse datasets w/ realistic partition
 - CV, NLP, RL tasks
 - Small/Medium/Large scales
 - Standardized data loader
- Use cases
 - Investigate convergence under realistic dist.
 - Pinpoint accuracy fairness across clients
 - Personalize models for different clients
 - ...

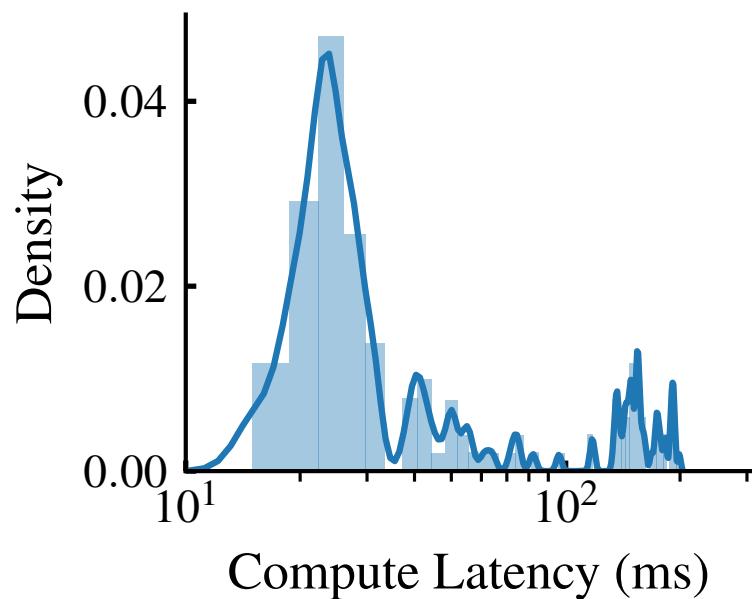
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Millions of Client System Traces

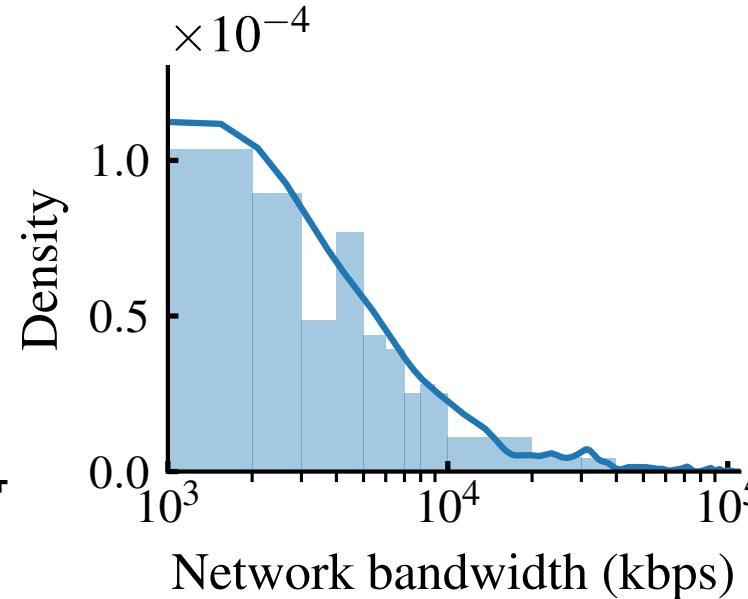


Heterogeneous computation/
communication speed

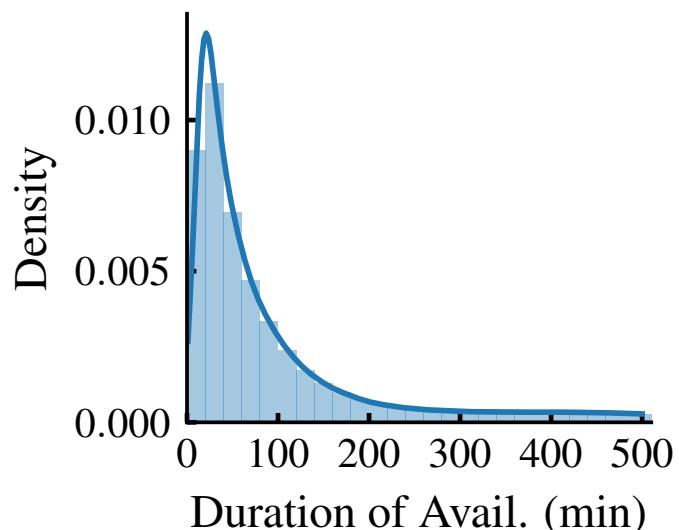
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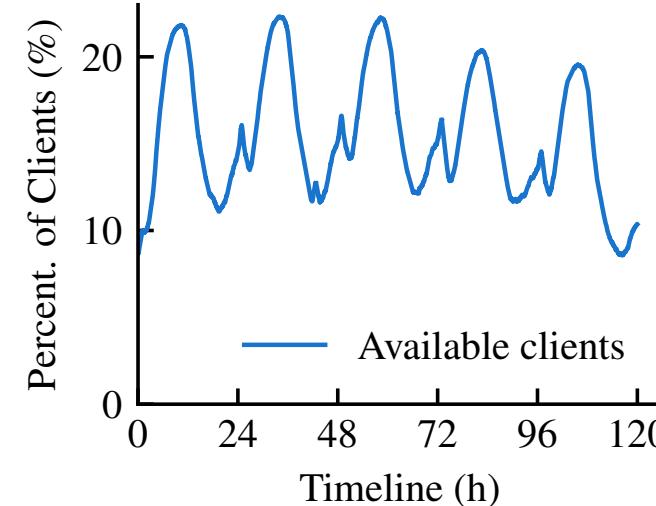
Compute Latency (ms)



Network bandwidth (kbps)



Duration of Avail. (min)



Available clients

Heterogeneous computation/
communication speed

Dynamics of client availability
in the wild

1

Realistic FL Datasets

Statistical client datasets

- ~20 datasets w/ real partition
- Various FL tasks/scales

Client system traces

- Client device speed
- Device availability over time

2

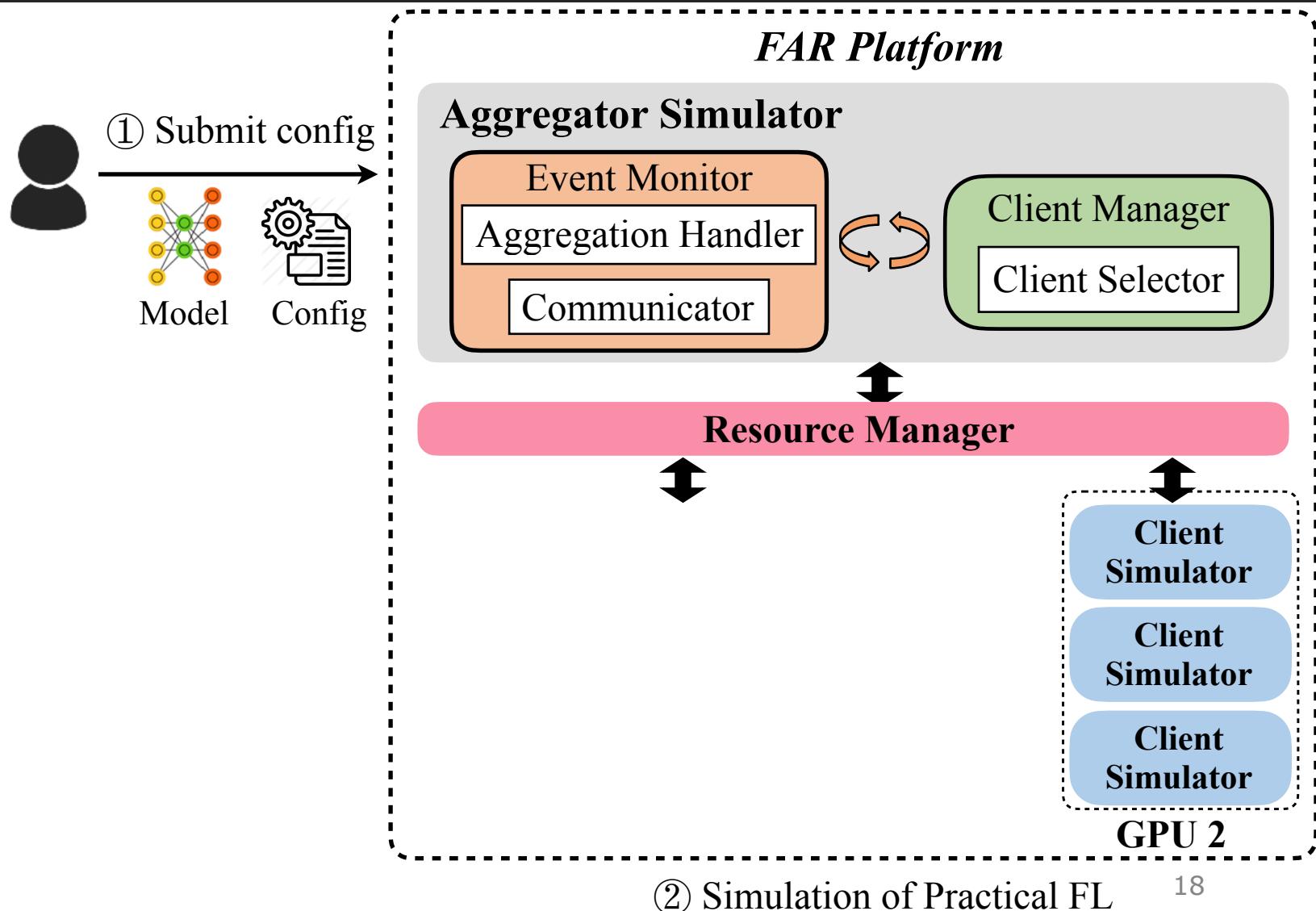
Scalable Eval Platform

3

Easy Development

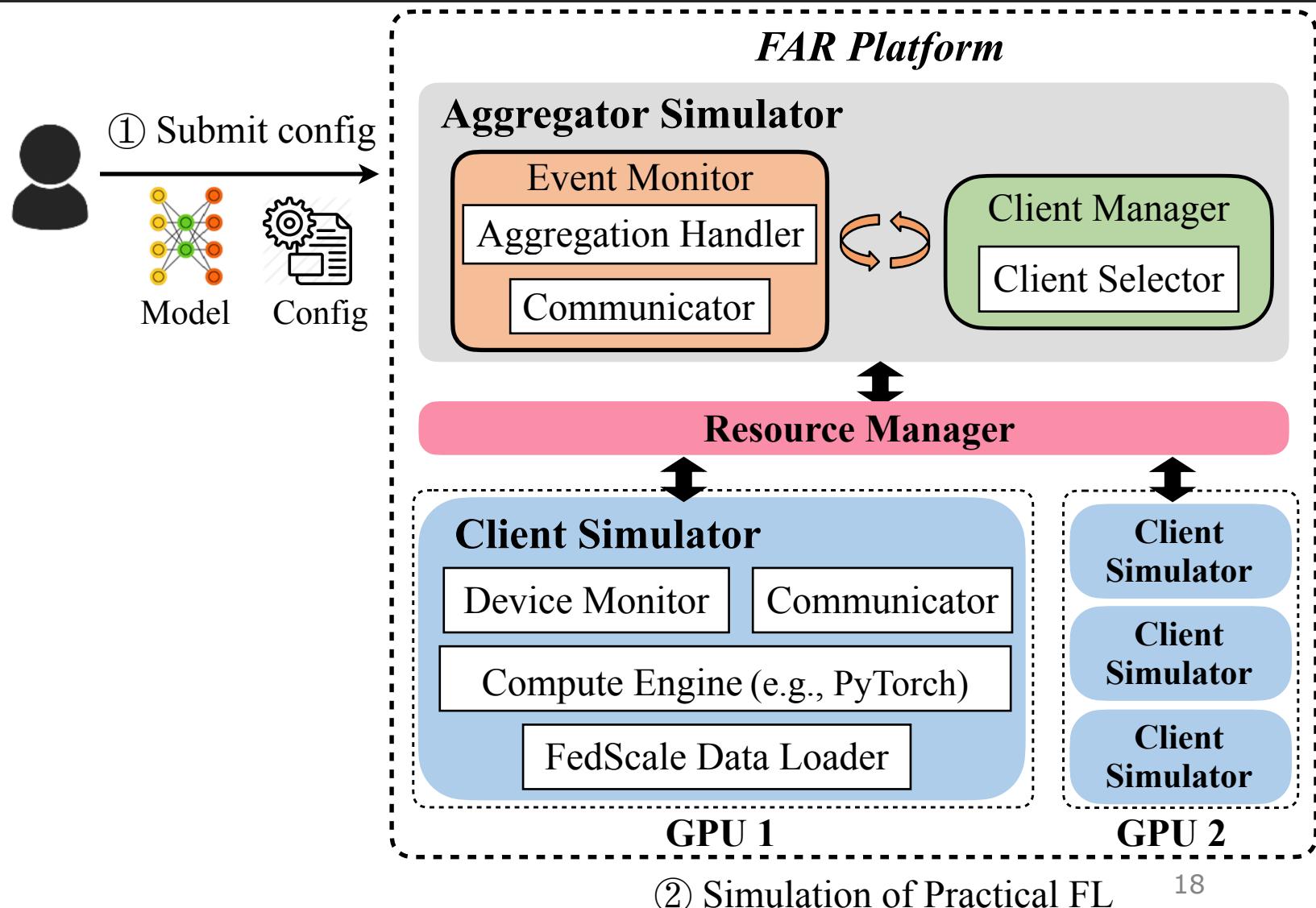
FAR: FedScale Automated Runtime

- Scalable eval platform
 - GPUs/CPPUs
 - High resource util.



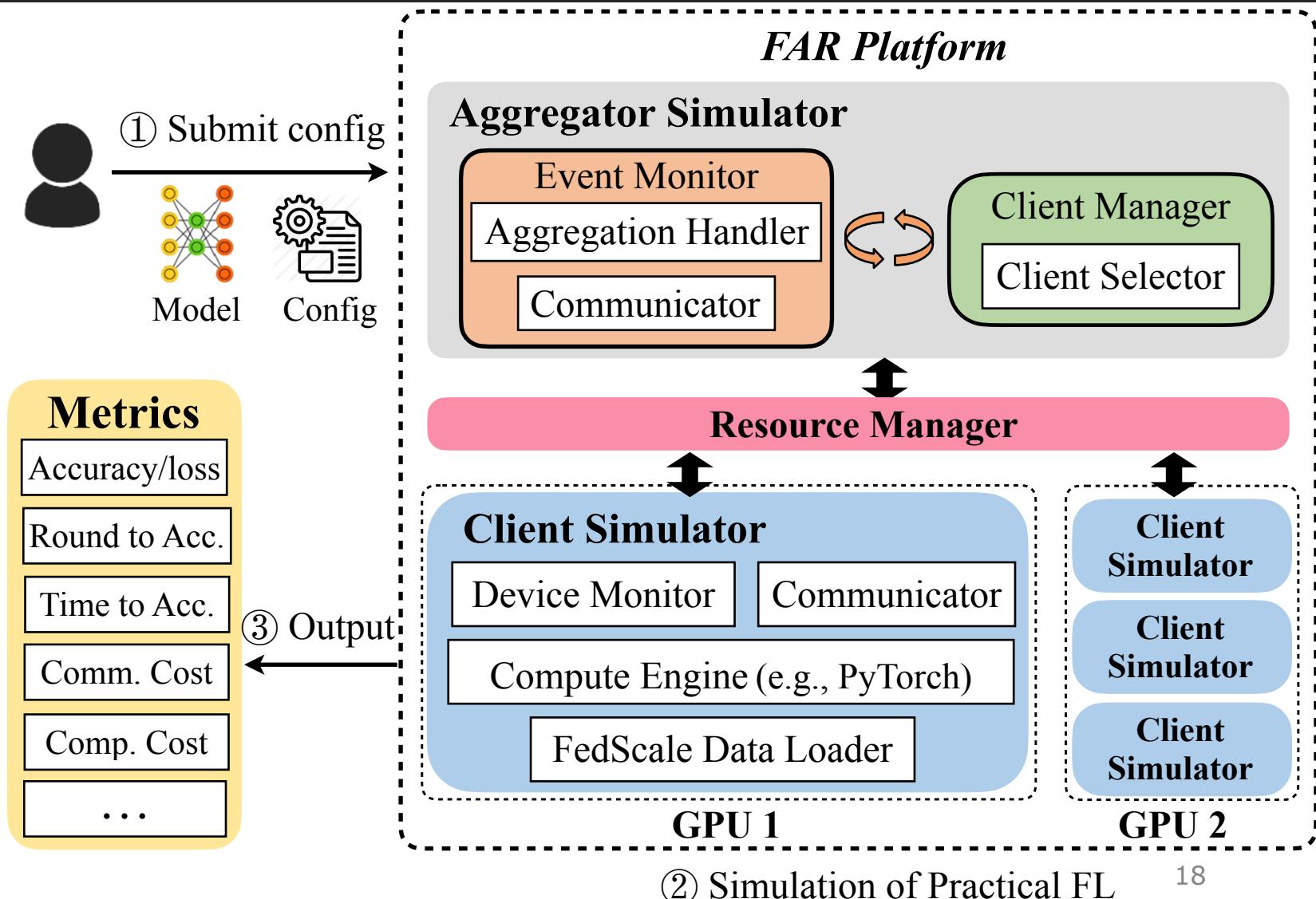
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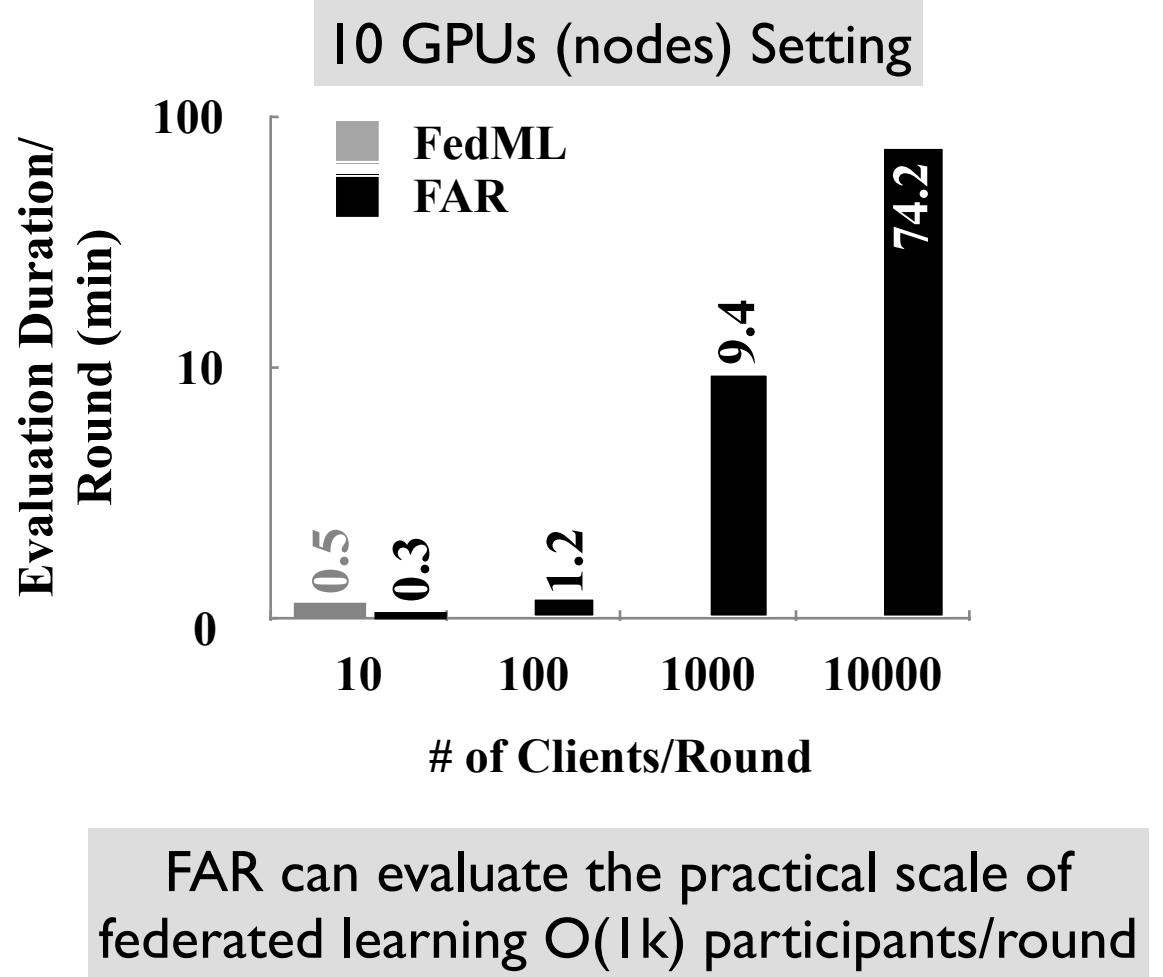
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- Practical FL runtime
 - Convergence
 - System duration



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FAR: Easily-Deployable Benchmarking

- Flexible APIs to automatically integrate new plugins
 - Little effort to customize/benchmark new designs

Module	API Name	Example Use Case
Aggregator	<code>round_completion_handler(*args)</code>	Adaptive/secure model aggregation
Simulator	<code>client_completion_handler(client_id, msg)</code> <code>push_msg_to_client(client_id, msg)</code>	Straggler mitigation Model compression
Client	<code>select_clients(*args)</code>	Client selection
Manager	<code>select_model_for_client(client_id)</code>	Adaptive model selection
Client Simulator	<code>train(client_data, model, config)</code> <code>push_msg_to_aggregator(msg)</code>	Local SGD/malicious attack Model compression

Some Example APIs

FAR: Easily-Deployable Benchmarking

- Flexible APIs to automatically integrate new plugins
 - Little effort to customize/benchmark new designs

```
from fedscale.core.client import Client

class Customized_Client(Client):
    # Customize the training on each client
    def train(self,client_data,model,conf):
        # Get the training result from
        # the default training component
        training_result = super().train(
            client_data, model, conf)

        # Clip updates and add noise
        secure_result = secure_impl(
            training_result)
        return secure_result
```

A few lines are enough for benchmarking

FAR: Easily-Deployable Benchmarking

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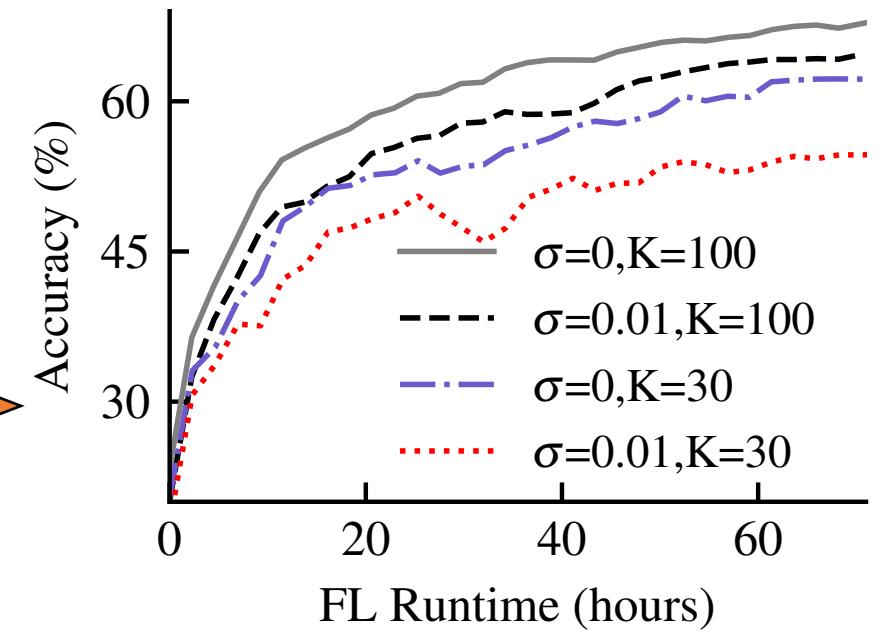
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Differential Private-SGD

σ (privacy target)
K (# participants/round)



A few lines are enough for benchmarking

FedScale can benchmark more realistic statistical/system performance

1

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Client system traces

- Client device speed
- Device availability over time

2

Scalable Eval Platform

Standardized benchmarking

- GPUs/CPUs
- Standalone/Distributed
- Practical FL runtime

3

Easy Development

Easily-deployable to plugins

- Flexible APIs
- Extensible to new traces
- Automated integration

1

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FedScale is open-source:

fedscale.ai

We welcome
your contributions!