

A Performance Evaluation of Federated Learning algorithms

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Presented by Simon Smith at DIDL'18

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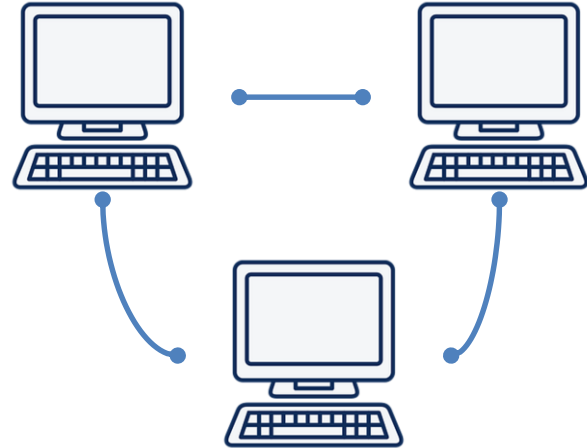
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What is Federated Learning (FL)?

- Distributed machine learning
 - Communicate a model, not data.

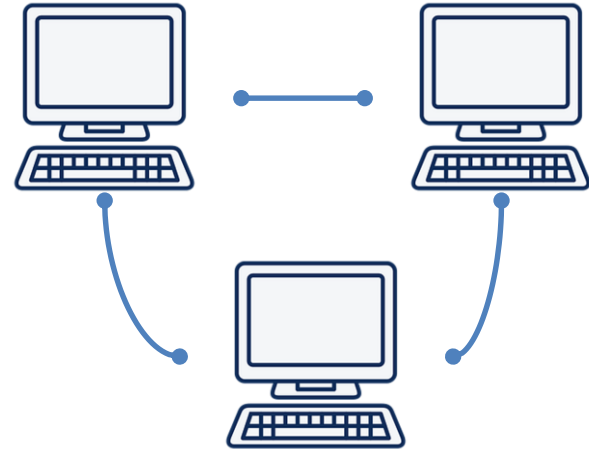
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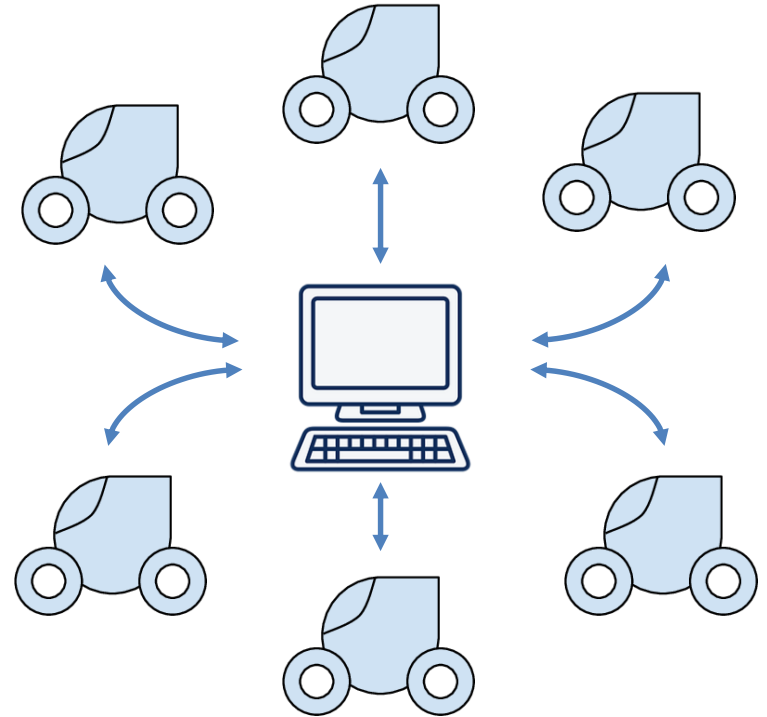
What is Federated Learning (FL)?

- Distributed machine learning
 - Communicate a model, not data.
- Massive number of clients
 - Slow, unreliable network
 - 250M connected vehicles by 2020¹



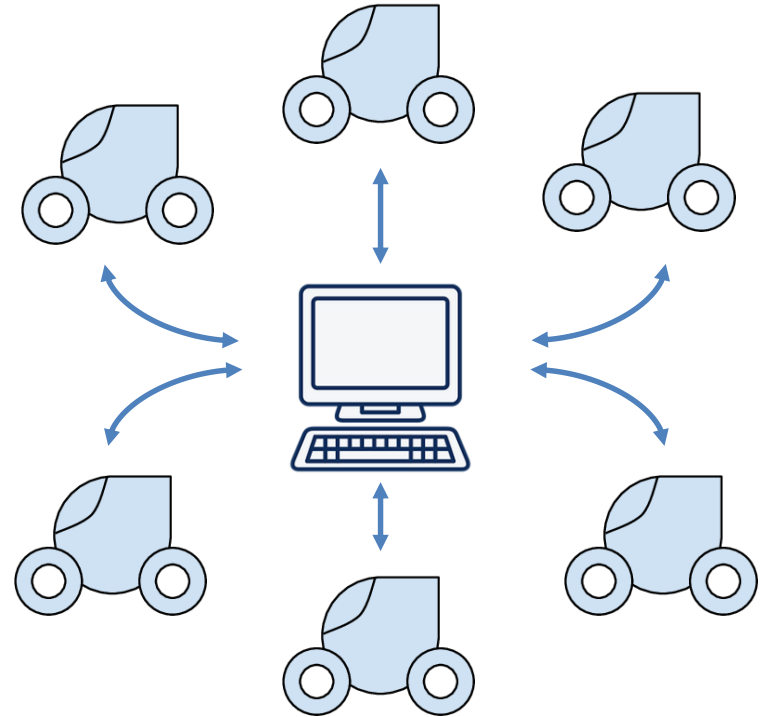
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- GDPR

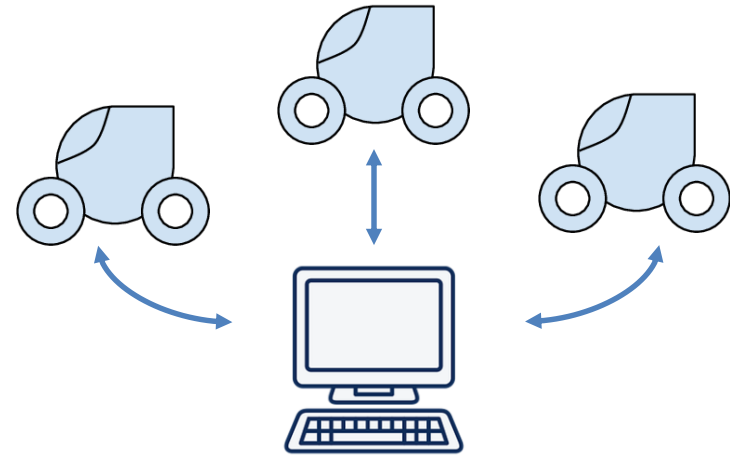


What have we done!?

- Implemented and compared three FL algorithms
- Compared with fully centralized approach

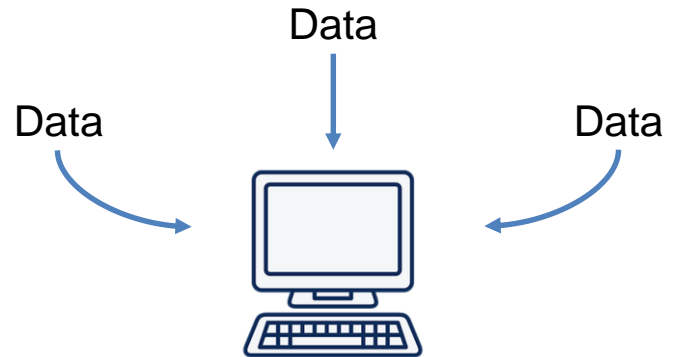
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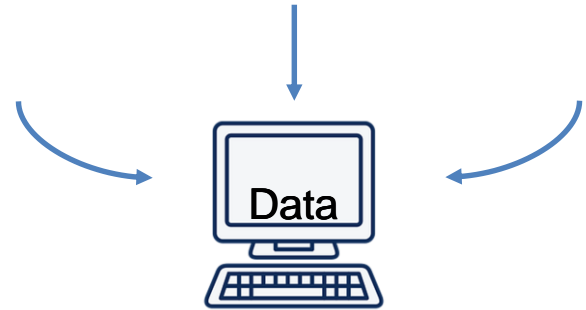
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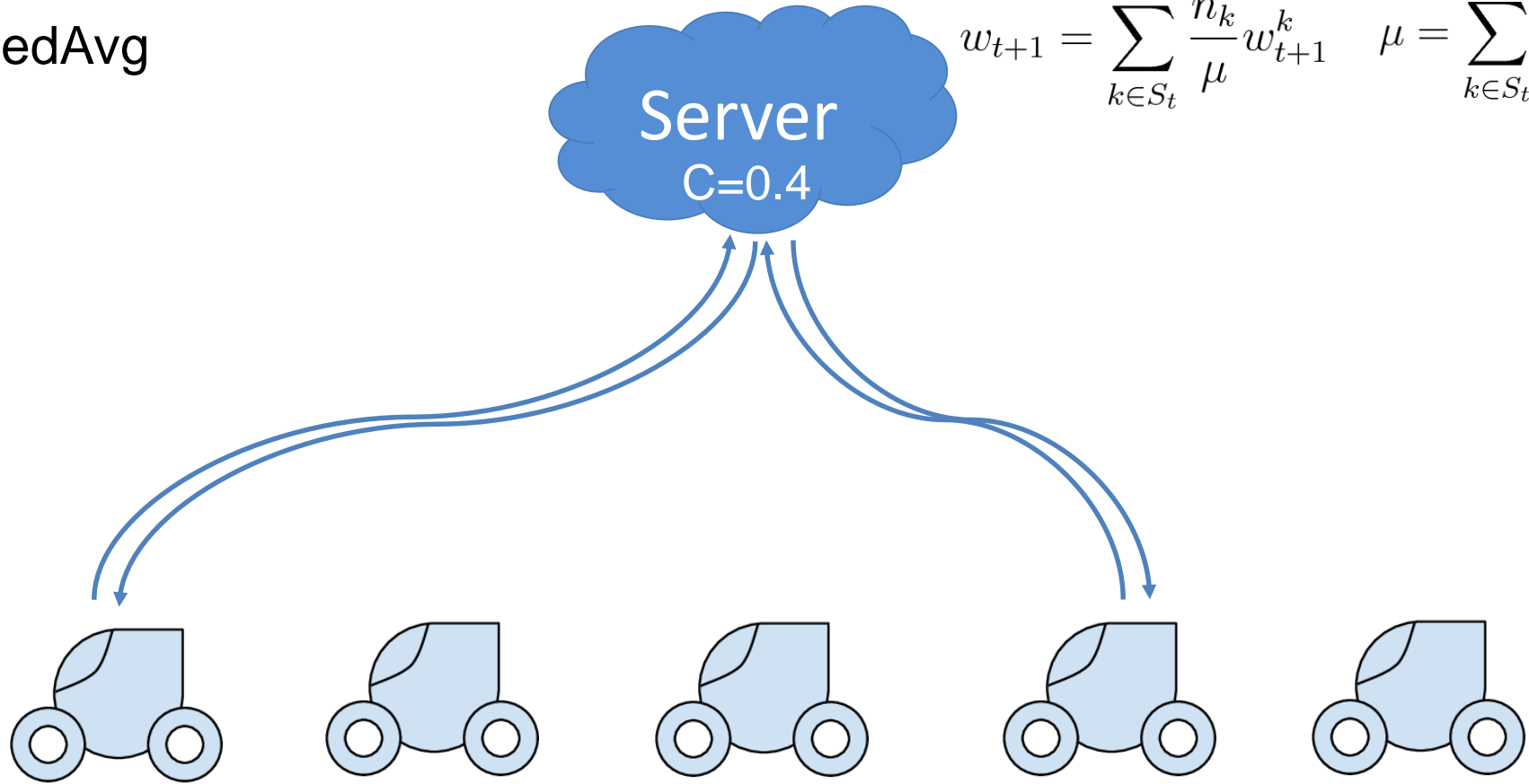
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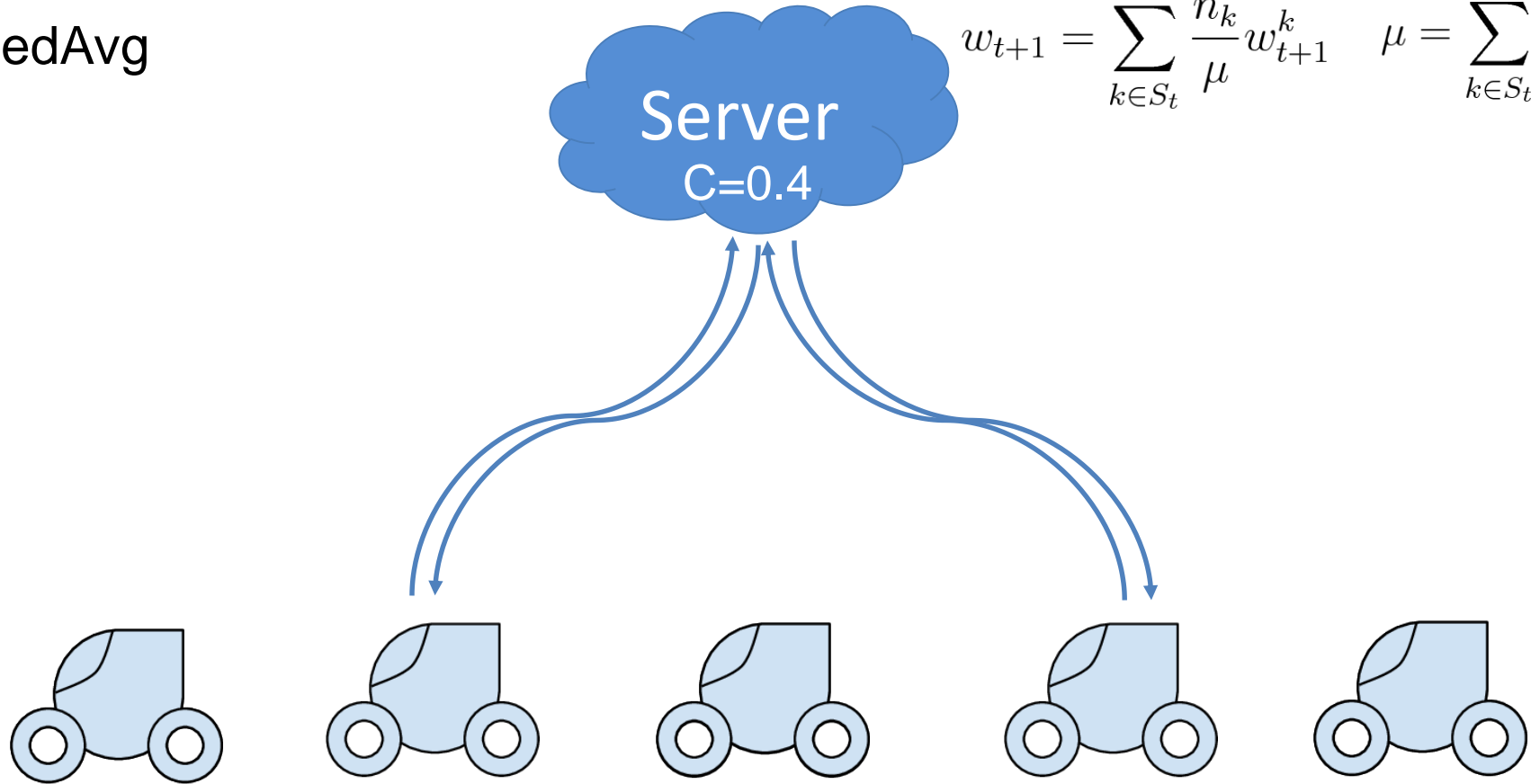
FedAvg

$$w_{t+1} = \sum_{k \in S_t} \frac{n_k}{\mu} w_{t+1}^k \quad \mu = \sum_{k \in S_t} n_k$$

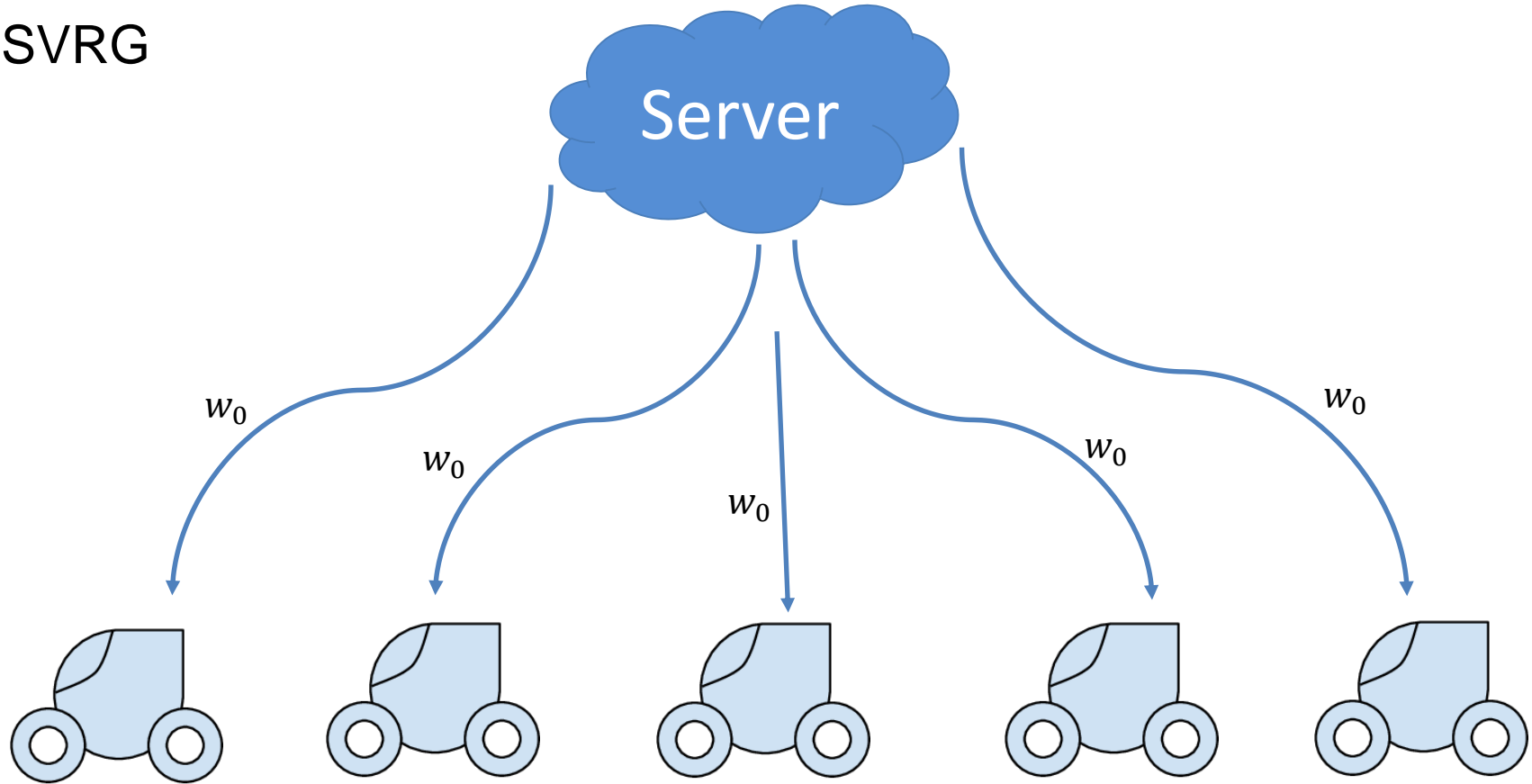


FedAvg

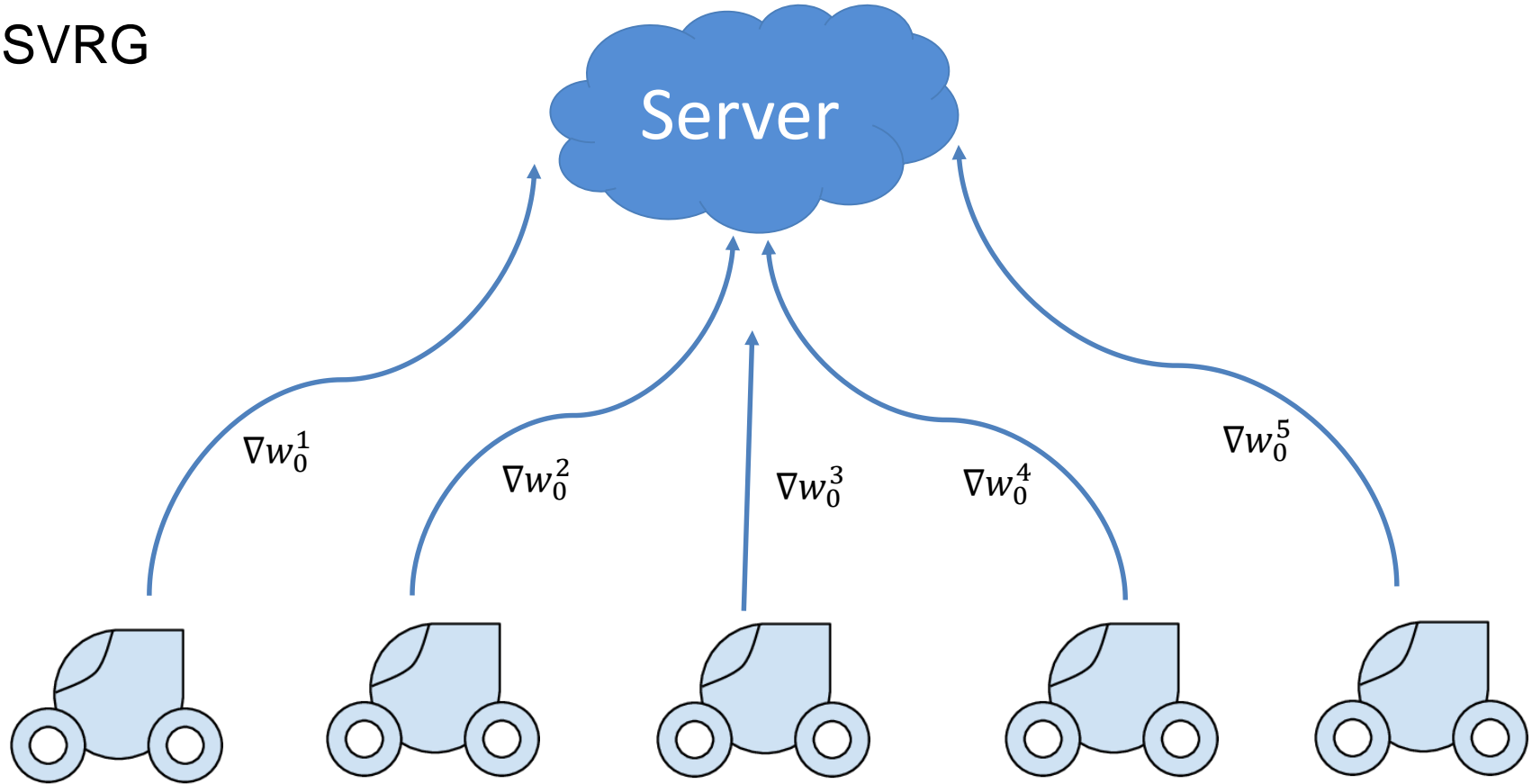
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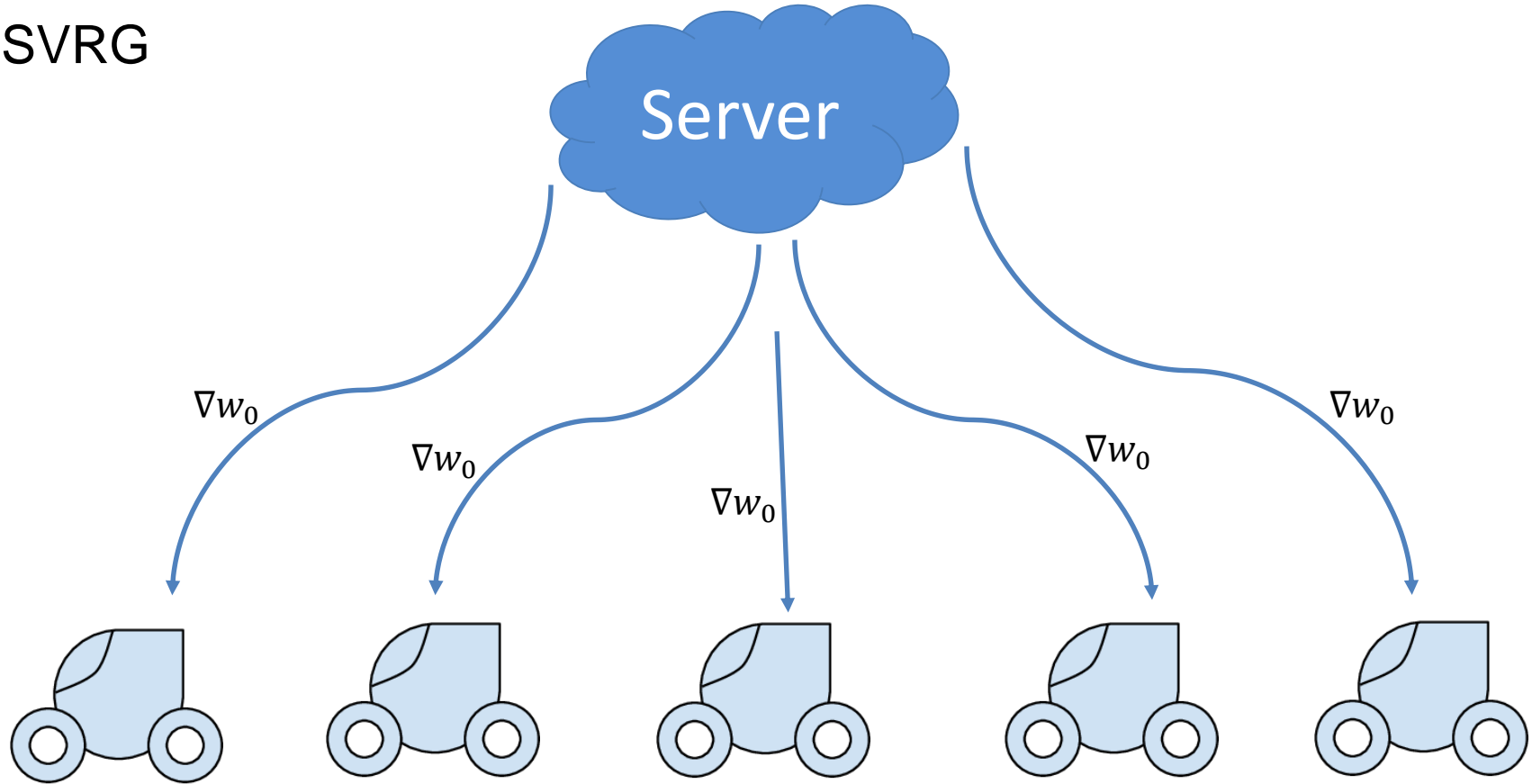
FSVRG



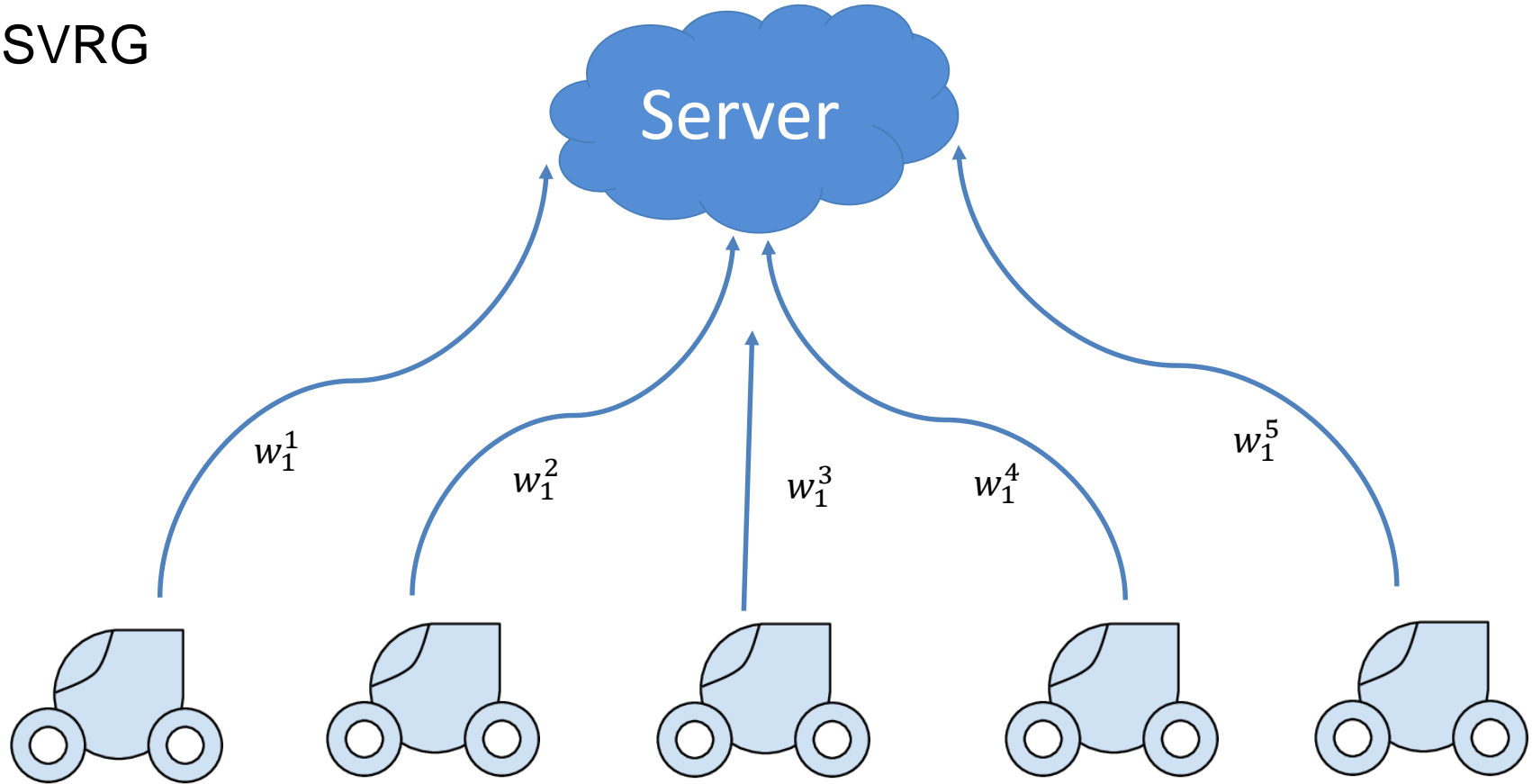
FSVRG



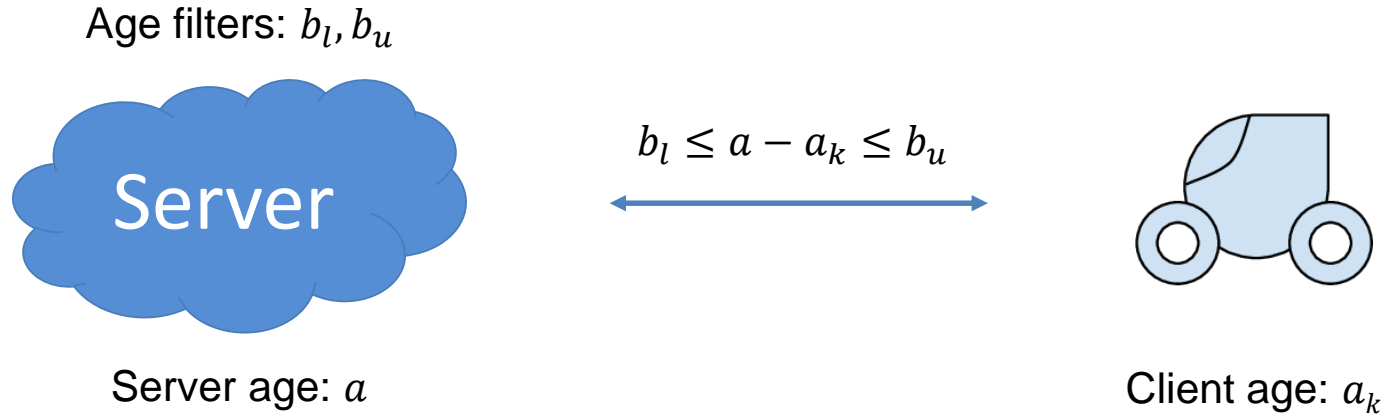
FSVRG



FSVRG



CO-OP



Algorithms

	Synchronous	Opt. Algorithm	New hyperparam.	Note
FedAvg	✓	SGD	C, E	C – fraction of clients E – epoch before upload
FSVRG	✓	SVRG	h	
CO-OP		SGD	b_l, b_u	“Age filters” - Mitigate staleness

Evaluation approach

MNIST digit recognition

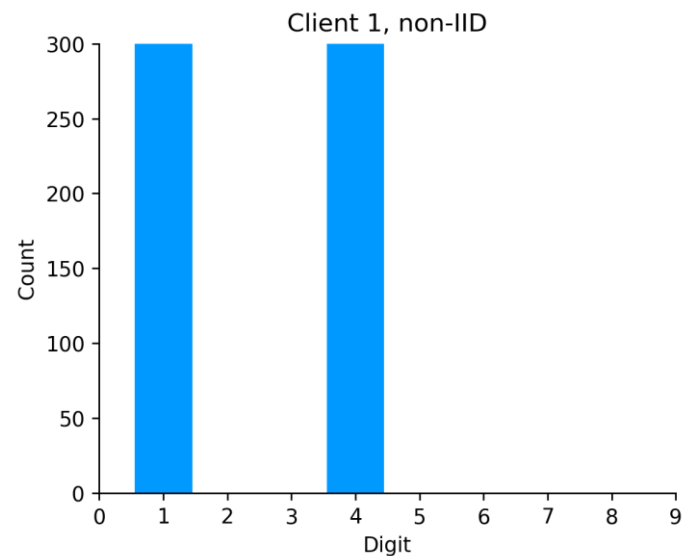
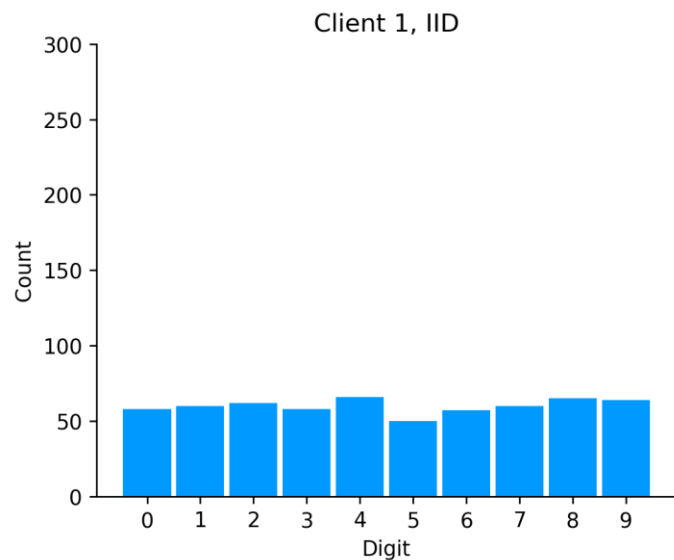
Feed-forward ANN with 2 hidden layers

100 clients



Evaluation approach

IID & non-IID partitionings

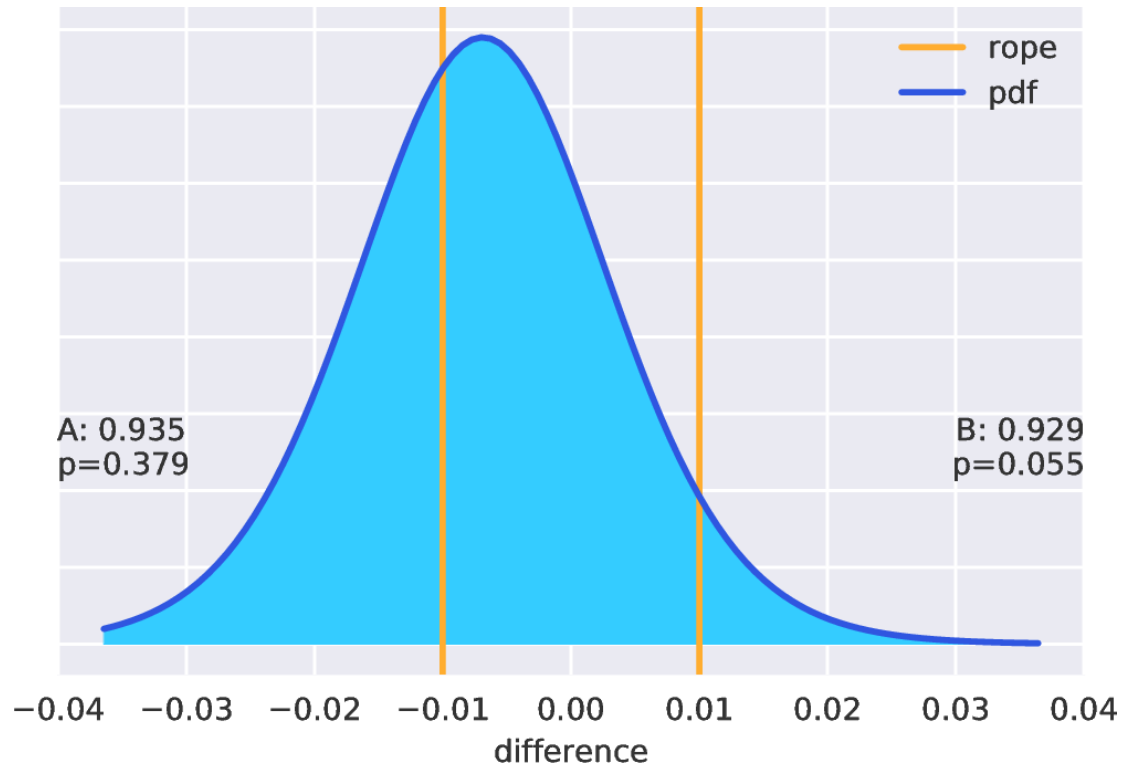


Evaluation approach

- Hyperparameter search
 - Learning rate, decay, epochs, batch size, global step size, age filter
- Cross-validation
 - We allow 10,000 uploads from 100 simulated clients

Bayesian comparisons

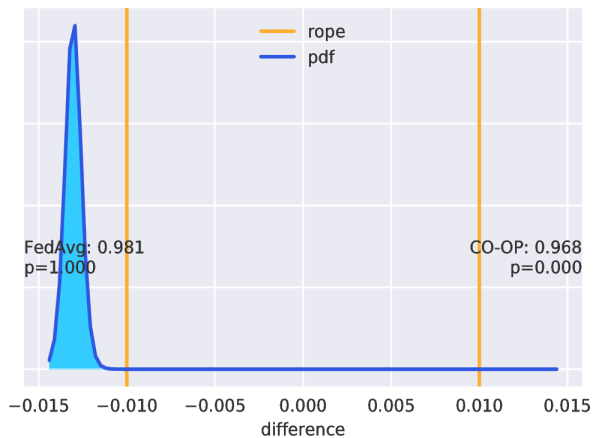
- x-axis shows *mean difference in accuracy* between **A** and **B**
- Region of practical equivalence (**rope**)
- Area is interpreted as a probability.



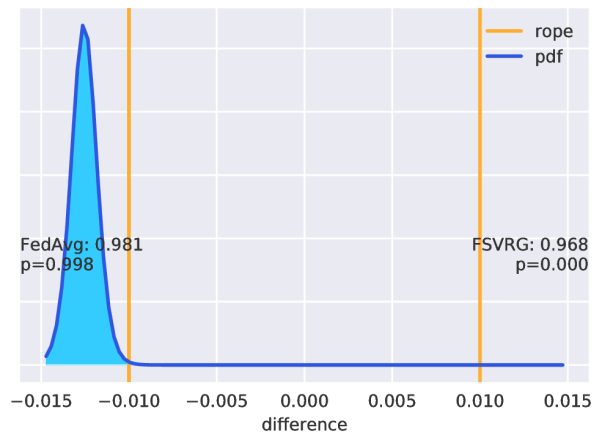
Benchmarking on IID data



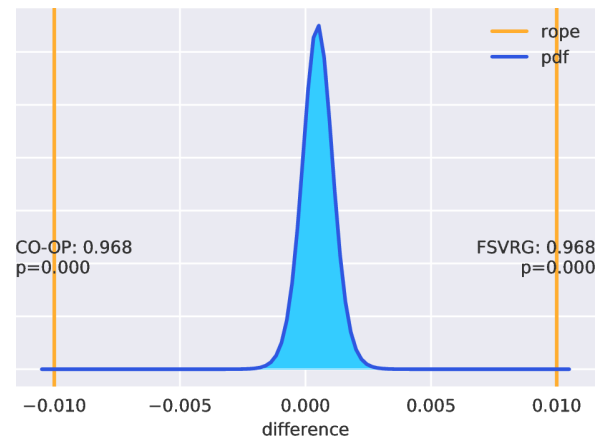
Results – Federated Learning IID



FedAvg vs CO-OP

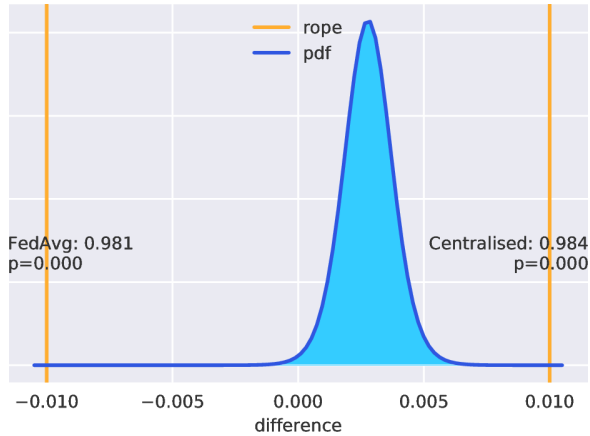


FedAvg vs FSVRG

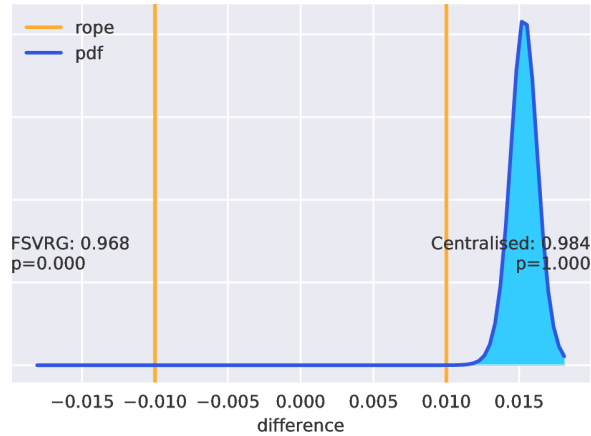


CO-OP vs FSVRG

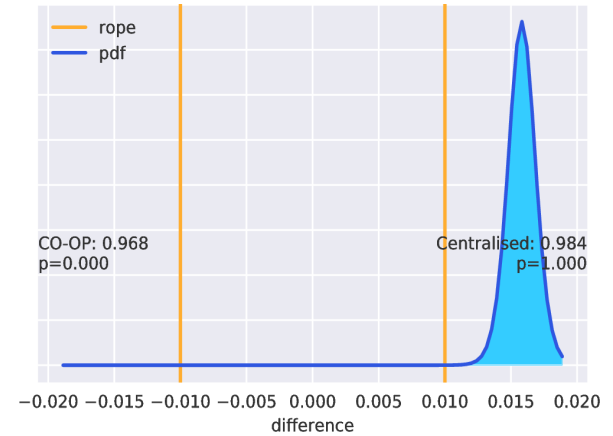
Results – Federated Learning IID vs Centralized Learning



FedAvg



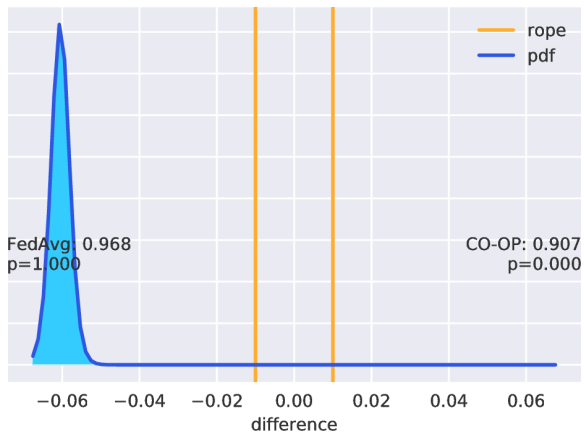
FSVRG



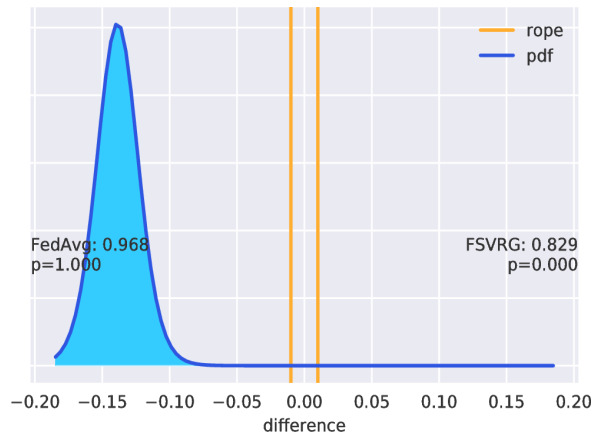
CO-OP

Benchmarking on non-IID data

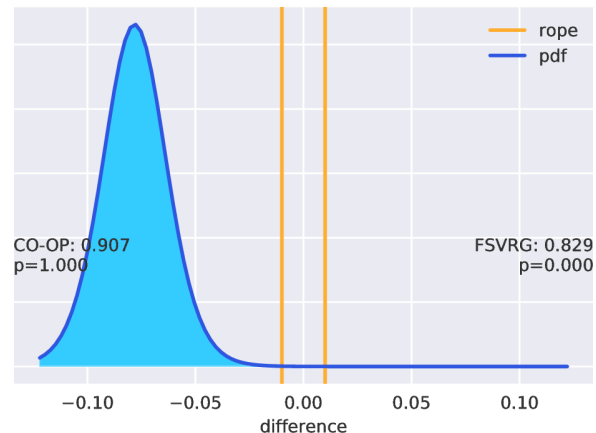
Results – FL non-IID



FedAvg vs CO-OP

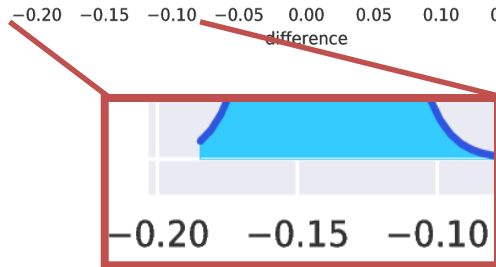
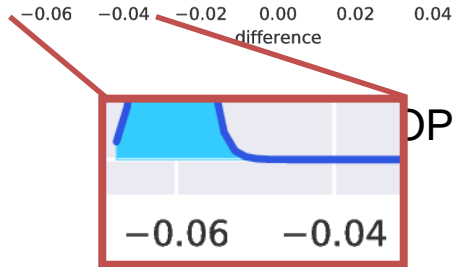
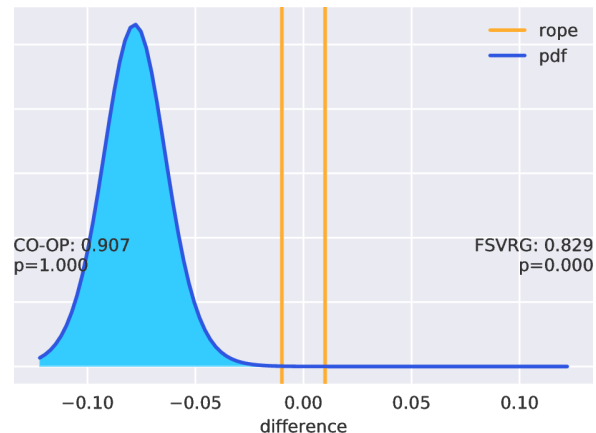
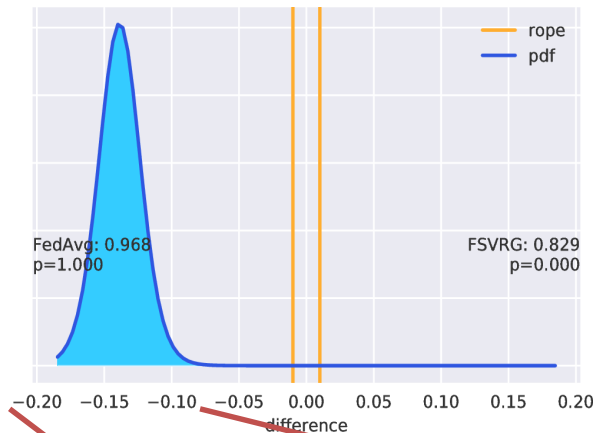
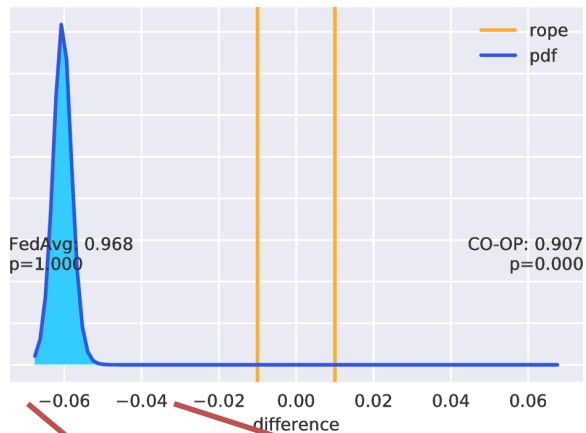


FedAvg vs FSVRG



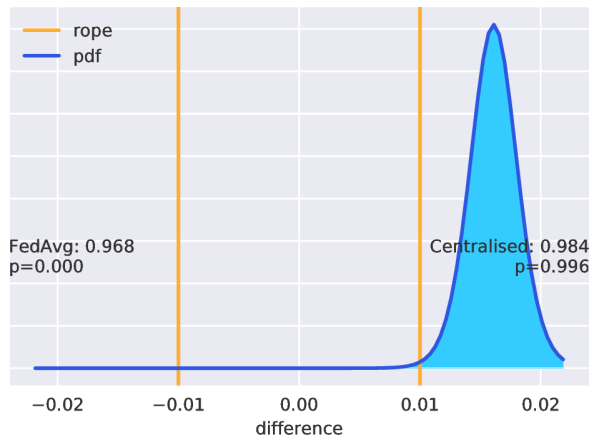
CO-OP vs FSVRG

Results – FL non-IID

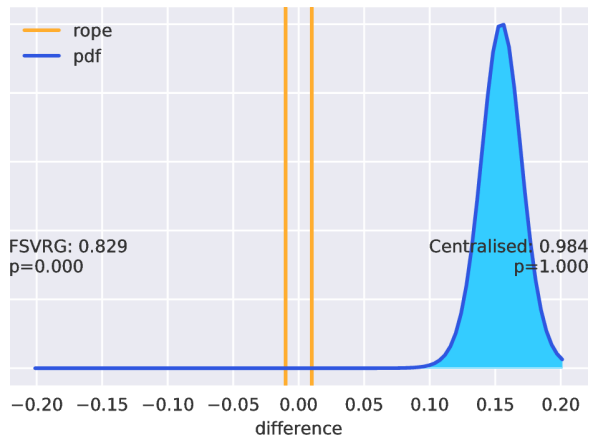


CO-OP vs FSVRG

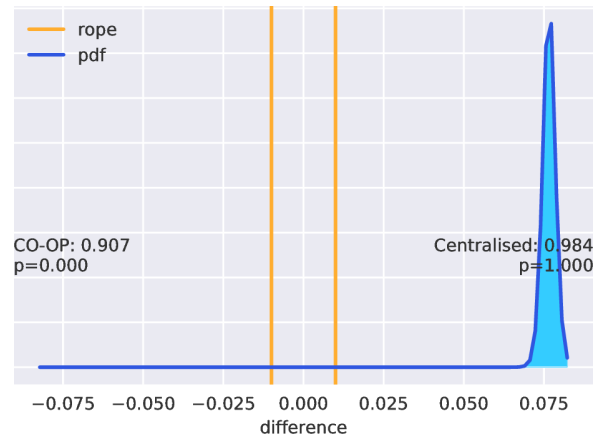
Results – FL non-IID vs Centralized Learning



FedAvg



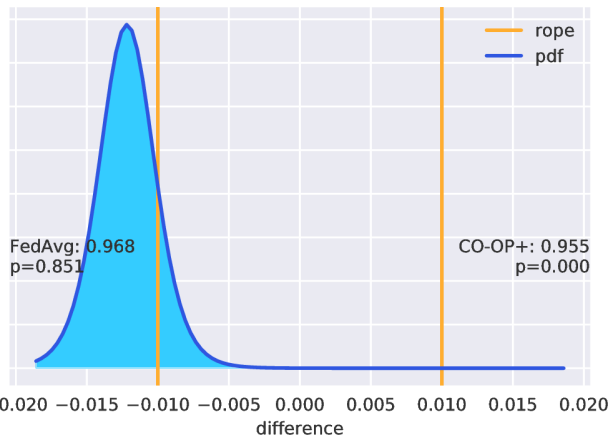
FSVRG



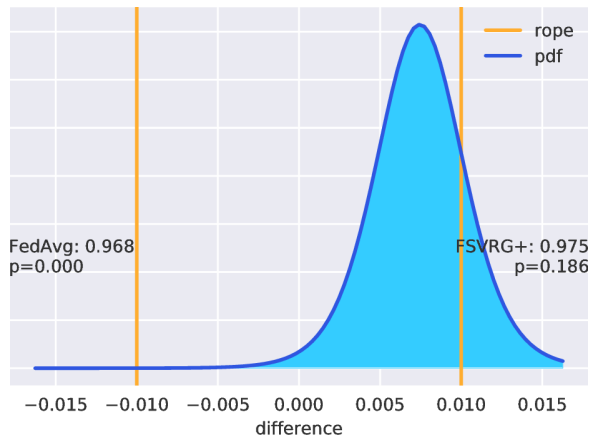
CO-OP

Allowing more communication for FSVRG and CO-OP

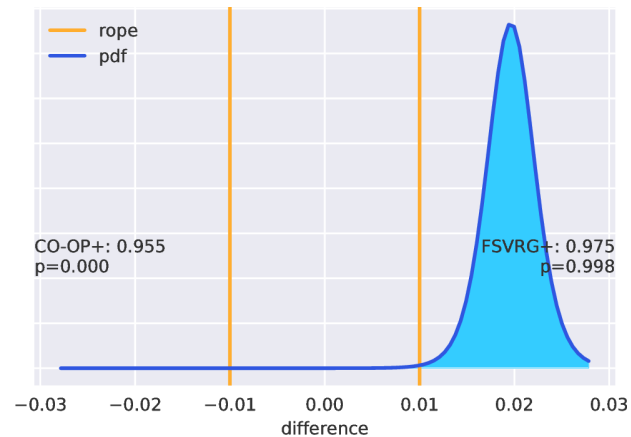
Results – FL non-IID; more uploads



FedAvg vs CO-OP^(x5)

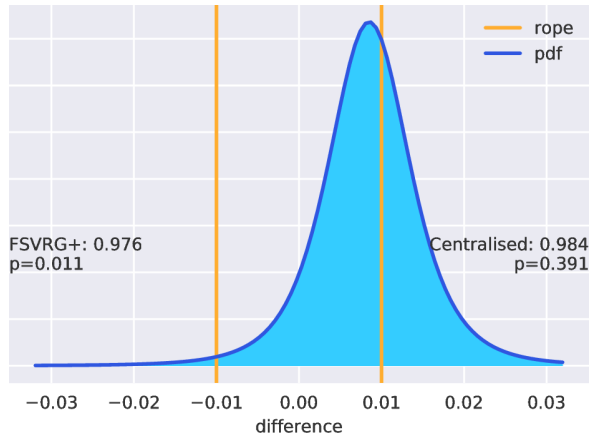


FedAvg vs FSVRG^(x10)

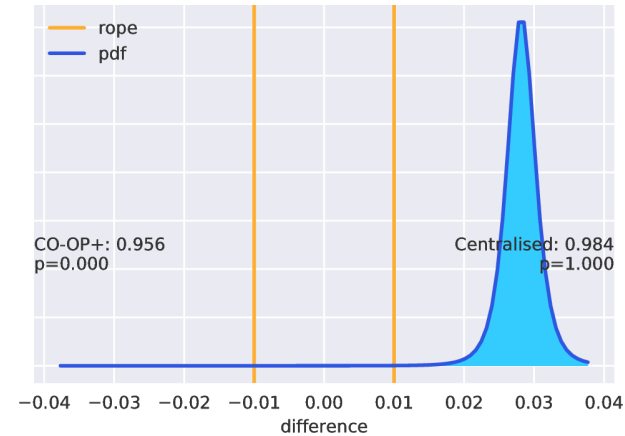


CO-OP^(x5) vs FSVRG^(x10)

Results – FL non-IID; more uploads vs Centralized Learning



FSVRG ($\times 10$)



CO-OP ($\times 5$)

Practical considerations

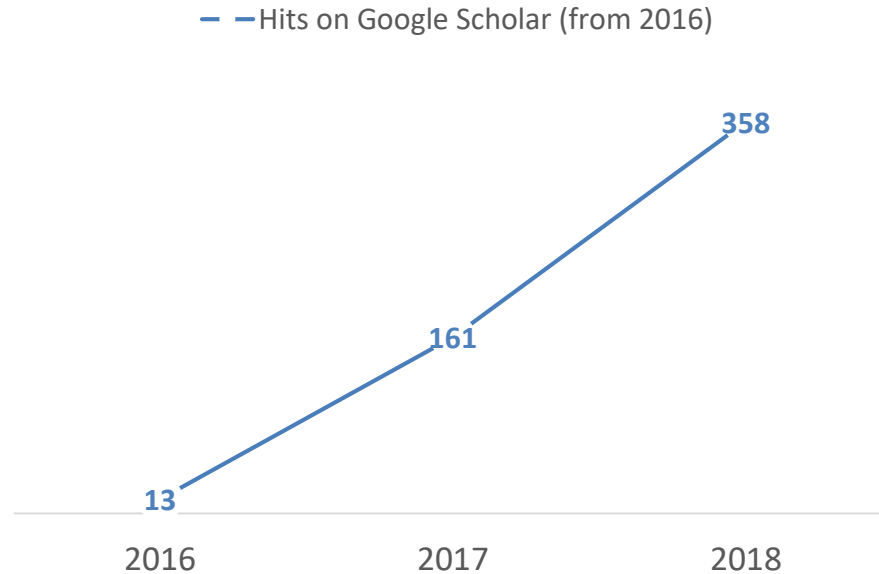
- FSVRG
 - Requires more communication per global update
- CO-OP
 - Age filters are difficult to tune

Future work

- Evaluate on multiple datasets
- Examine unevenly distributed data
 - i.e. a few cars hold most of the data
- New algorithms



Algorithm + "Federated Learning"



What has happened since?

- Non-IID is still an issue [\[1,2\]](#)
- More privacy [\[3,4\]](#)
- New Algorithms
 - Asynchronous FL [\[5\]](#)
 - Dynamic Averaging Protocol [\[6\]](#)
 - Federated Kernelized Multi-task Learning [\[7\]](#)

Thank you

References

(Non-IID)

- [1] **Federated Learning with Non-IID Data**, Zhao et al., 2018 ([arXiv:1806.00582](https://arxiv.org/abs/1806.00582))
- [2] **Communication-Efficient On-Device Machine Learning: Federated Distillation and Augmentation under Non-IID Private Data**, Jeong et al., 2018 ([arXiv:1811.11479](https://arxiv.org/abs/1811.11479))

(Privacy)

- [3] **Biscotti: A Ledger for Private and Secure Peer-to-Peer Machine Learning**, Shayan et al., 2018 ([arXiv:1811.09904](https://arxiv.org/abs/1811.09904))
- [4] **cpSGD: Communication-efficient and differentially-private distributed SGD**, Agarwal et al., 2018 ([arXiv:1805.10559](https://arxiv.org/abs/1805.10559))

(Algorithms)

- [5] **Asynchronous Federated Learning for Geospatial Applications**, Sprague et al., DMLE'18, <https://dmle.iais.fraunhofer.de/papers/sprague2018asynchronous.pdf>
- [6] **Efficient Decentralized Deep Learning by Dynamic Model Averaging**, Kamp et al., 2018 ([arXiv:1807.03210](https://arxiv.org/abs/1807.03210))
- [7] **Federated Kernelized Multi-Task Learning**, Caldas et al., Poster at SysML 2018, <https://www.sysml.cc/doc/30.pdf>

