

Terraform: Resolving Heterogeneity in Federated Learning through Client Ranking

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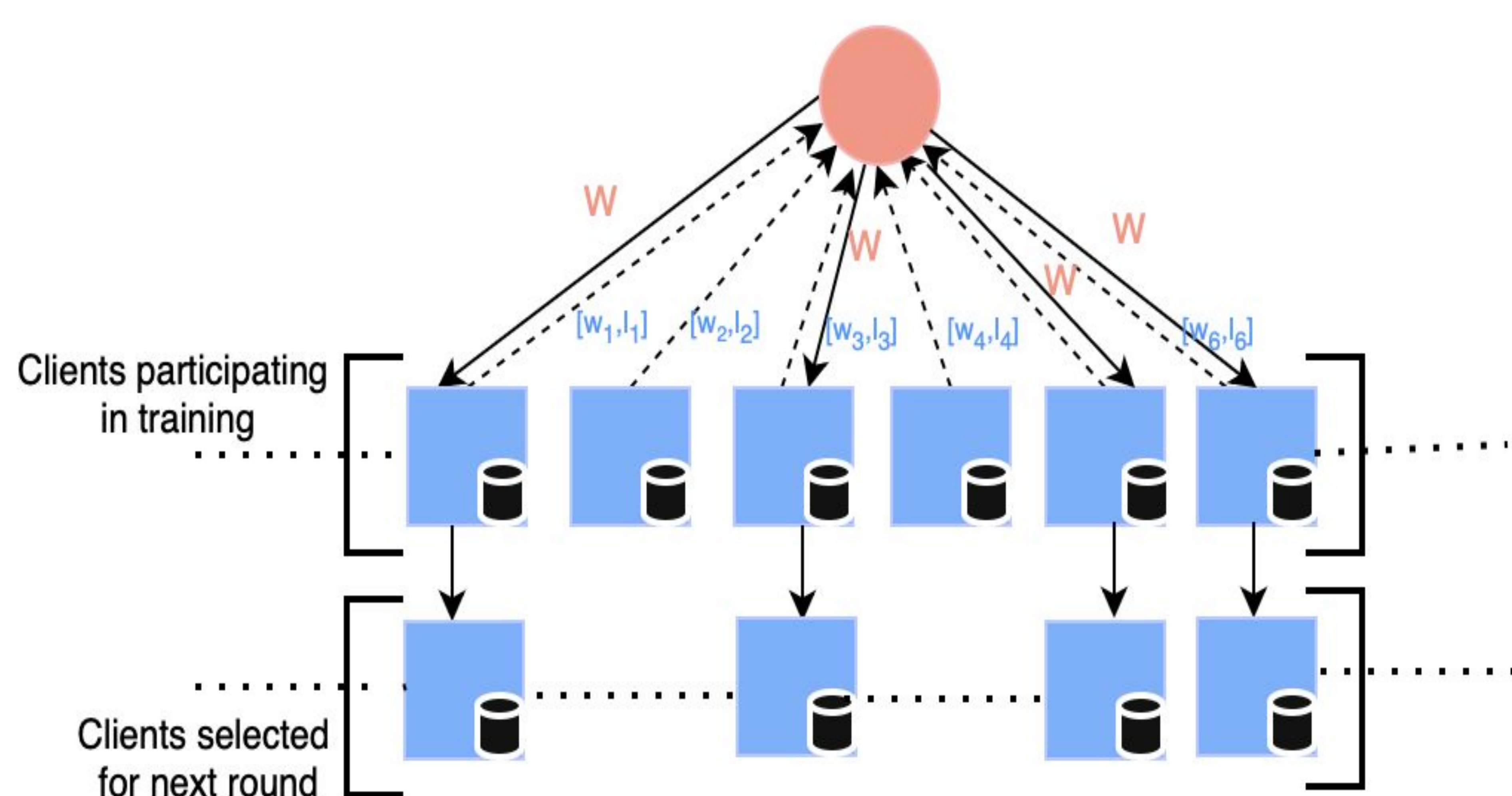
Problem

- Federated learning (FL) algorithms yield lower accuracy than centralized models due to **uneven, heterogeneous data distribution across clients**.
- Existing FL algorithms make following trade-offs to improve accuracy:
 - Fairness** – ignore clients with small, unique data.
 - Scalability** – require high, inefficient compute
 - Privacy** – each client assumes access to all the data, not just the local ones.

FedAvg with Sampling?

- Random client sampling:** Does not guarantee the selection of clients with unique data.
- Data volume based sampling:** Cannot adapt to variations in data distributions across clients.
- Loss based sampling:** Limited utilization of model update signals for client selection.

Solution: Gradient Variance based Client Selection



- Post training, each client sends the gradients of its last layer to the server.**
 - Reflect the client specific training dynamics.
 - Preserves privacy.
- Server computes the magnitude of each client's gradient.**
 - High magnitude can indicate the underrepresented, complex local distributions.
- Select a subset of magnitudes that minimizes the overall variance across the clients.**
 - Reduces model inconsistency.
 - Improves global convergence.
 - Continually adapts client selection.

Open Questions

- Is this approach robust across vision, NLP, and multimodal tasks?
- Can variance be approximated to reduce the compute further?

Preliminary Results

FL Algorithm	Accuracy baseline(SD)	Accuracy ours(SD)
FedProx	77.70(±0.18)	81.14 (±0.15)
FedALA	77.69(±0.21)	80.86 (±0.14)
FedSR	79.89(±0.13)	82.99 (±0.12)
FedBabu	75.66(±0.28)	79.29 (±0.20)
ElasticAgg	74.03(±0.19)	79.56 (±0.07)
PeFLL	85.03(±0.17)	88.50 (±0.11)
PFedSim	74.43(±0.09)	79.15 (±0.05)

Test Accuracy after 100 rounds of training on FEMNIST dataset.