1 Summary (50% : half page)This paper proposes a novel federated learning algorithm called N-FedAvg to address some limitations of the traditional FedAvg approach. The motivation is to improve federated learning performance in terms of accuracy, efficiency, and security.

The key contributions of this paper are introducing sequential client selection, dynamic learning rates through cosine annealing, and model compression via sparsity. Sequential client selection reduces randomness and ensures all client data participates. Cosine annealing learning rates speed up convergence. Sparsity reduces communication overhead and improves security.

The methodology involves algorithm development and experimentation. The N-FedAvg algorithm is presented in detail. It uses sequential client selection to reduce randomness. Cosine annealing is applied to dynamically set the learning rate. Sparsity compresses models before transmission. Experiments are conducted using PyTorch on the CIFAR-10 dataset. N-FedAvg is compared to FedAvg and centralized training. 20 clients are simulated with 2 selected per round. The global model is initialized with ResNet50. Hyperparameters are set including 200 global epochs. Results compare convergence speed, accuracy, and loss function value.

In conclusion, this paper proposes N-FedAvg that applies sequential client selection, cosine annealing learning rates, and sparsity to improve federated learning. Experiments show N-FedAvg converges faster and achieves higher accuracy and lower loss compared to FedAvg.

2 Limitations (30% : quarter page)

- One limitation is that experiments only use the small, simple CIFAR-10 dataset. The algorithm should be evaluated on larger and more complex benchmarks like ImageNet to better simulate real-world conditions. The small dataset means models converge quickly so hyperparameters may not be ideal. Testing on datasets more representative of applications would strengthen results.
- Another limitation is the client simulation lacks heterogeneity present in real systems. The paper simulates 20 clients with 2 selected per round, but does not model factors like non-IID data, varied capabilities, and unreliable networking. Real implementations have more dynamic environments the simulation does not capture. Evaluating on an open-source framework using real devices could give more insights into real-world performance.

3 Synthesis (20% : quarter page):

- In healthcare, federated learning is used to build models from sensitive medical data across institutions without sharing the data. N-FedAvg's sequential client selection could ensure each hospital's data is included in the model. Dynamic learning rates could help converge on optimal models faster. Sparsity improves security and efficiency for healthcare networks.
- For finance applications like fraud detection, N-FedAvg's techniques like sparsity could allow models to be built from transaction data across banks without compromising sensitive information. Faster convergence through dynamic learning rates enables more timely fraud alerts.