

Population Scaling or Data Dilution?

Dynamics of Local Topology Evolution in Decentralized Learning

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Abstract

Scaling decentralized learning changes not only the number of clients N , but also the dynamics of information propagation and consensus. We argue that the effect of increasing N cannot be understood in isolation, because data allocation, topology-dependent mixing, and communication capacity may change simultaneously. We study these coupled effects on CIFAR-10 with $N \in \{10, 50, 100, 200\}$, comparing a degree-two Ring, a Static Random graph, and Local-First Heuristic Evolution (LFHE), a locally adaptive topology process based on friend-of-friend discovery. The Ring provides an analytically transparent failure mode: its Metropolis spectral gap decays as $\Theta(N^{-2})$, implying progressively slower contraction of model disagreement as the population grows. Experiments show that holding the nominal local dataset size fixed substantially reduces the apparent population penalty observed when a fixed total dataset is divided among more clients. The remaining degradation depends strongly on communication structure: Ring enters a high-disagreement regime, whereas Static Random and LFHE remain close to consensus. Increasing LFHE's degree threshold further improves accuracy and consensus, but at a substantially higher model-transmission cost. These results show that decentralized scaling is governed by coupled learning and communication dynamics, rather than by the number of clients alone.

1 Introduction

Decentralized learning replaces server aggregation with peer-to-peer model exchange, building on distributed optimization over communication graphs [4, 6, 7, 11]. Without a central coordinator, optimization becomes directly coupled to the communication topology: the graph structure and mixing weights determine how rapidly information propagates and local models approach consensus [2, 8, 9]. When the topology itself adapts during training, this dependence becomes bidirectional. Model states influence which edges are created or removed, the resulting graph determines subsequent mixing, and mixing in turn changes the model states that guide future topology updates.

Understanding how such systems scale with the number of clients N is difficult because several resources may change simultaneously. Under a fixed total dataset, increasing N enlarges the communication network while reducing the amount of data assigned to each client. Adaptive sparse graphs introduce a second scaling dimension: if their admissible degree grows with N , larger populations also receive greater communication and mixing capacity. Consequently, an observed scaling curve may reflect data allocation, topology-dependent mixing, communication capacity, or a combination of all three. Distinguishing these effects is essential because the convergence of decentralized optimization depends directly on the nontrivial spectrum of the communication operator [1, 2, 9, 12].

Recent work has explored adaptive peer selection and communication topology under heterogeneous data, including performance-based neighbor selection [10] and diversity-driven rewiring [3]. Our focus is complementary: we study how population size, data allocation, and communication capacity jointly shape the dynamics of decentralized learning. We compare three communication structures: a degree-two Ring, which provides an analytically transparent mixing bottleneck; a Static Random graph, which serves as a fixed sparse reference; and Local-First Heuristic Evolution (LFHE), a locally adaptive topology process based on two-hop friend-of-friend (FoF) discovery. For LFHE, we separately study a fixed degree threshold and a population-scaled threshold, allowing us to distinguish the effects of population growth from those of increasing communication capacity.

Our contributions are threefold. First, we show that the apparent population penalty depends strongly on data allocation. For LFHE, the accuracy loss from $N = 50$ to $N = 200$ decreases from 14.14 to 3.68 percentage points when moving from a fixed-total regime to one with a fixed nominal local dataset size. Second, we characterize a locality–communication trade-off: bounded local degree limits communication, but causes the

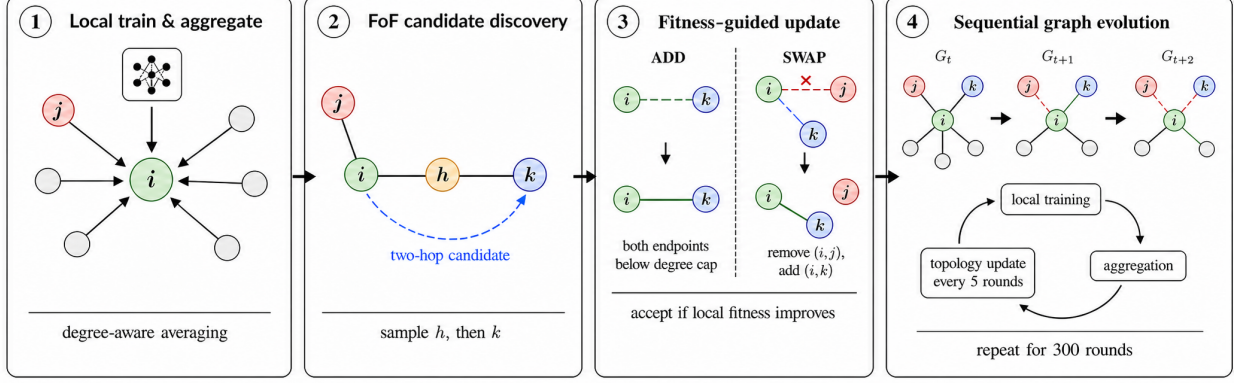


Figure 1: LFHE mechanism. Client i discovers a two-hop FoF candidate k , evaluates a locally improving addition or edge replacement, and sequentially commits accepted updates.

fraction of the population visible through two-hop discovery to shrink with N ; increasing the degree threshold expands both local search and mixing capacity, at a rapidly growing communication cost. Third, topology, model-disagreement, and communication-normalized trajectories reveal how these resource choices produce distinct graph-model regimes. Together, these results shift the scaling question from *how accuracy changes with N* to *which data and communication resources must scale with N to preserve effective decentralized learning*.

2 Local Topology Evolution Under Scaling

Let $G_t = (V, E_t)$ denote the communication graph and $W_t = (w_{1,t}, \dots, w_{N,t})$ the client models. Each communication round performs local optimization followed by graph-dependent mixing,

$$\widetilde{W}_t = \mathcal{L}(W_t; \xi_t), \quad W_{t+1} = P(G_t) \widetilde{W}_t. \quad (1)$$

Every $H = 5$ rounds, LFHE additionally applies $G_{t+1} = \mathcal{R}_t(G_t, W_{t+1})$; otherwise the graph is unchanged. The learning system is therefore coupled: G_t determines model mixing, while W_t provides the local signals used to evolve the topology.

Local topology evolution. Client i evaluates

$$f_i = (1 - \beta_t)C_i + \beta_t D_i - 0.1 d_i / D_{\max}, \quad \beta_t = e^{-0.01t}, \quad (2)$$

where C_i measures representation disagreement with current neighbors and D_i measures cosine mismatch with their mean representation. Client i samples $h \in \mathcal{N}_i$, then $k \in \mathcal{N}_h \setminus (\mathcal{N}_i \cup \{i\})$. Improving candidates are added when online degree conditions permit; otherwise LFHE evaluates a one-edge replacement. At each topology epoch, initiators are processed once in a fixed sequential order; each initiator evaluates one FoF candidate and commits at most one accepted add-or-swap operation before the next initiator observes the updated graph. The threshold $D_{\max}$ regulates online edge acquisition and therefore controls the capacity available to topology evolution.

Local visibility. If $\bar{d}_t = \max_i d_i(G_t)$, the two-hop candidate set satisfies

$$|\mathcal{C}_i^{(2)}(t)| \leq d_i(t)(\bar{d}_t - 1), \quad \frac{|\mathcal{C}_i^{(2)}(t)|}{N-1} \leq \frac{\bar{d}_t(\bar{d}_t - 1)}{N-1}. \quad (3)$$

With bounded local degree, relative FoF visibility therefore shrinks as $O(N^{-1})$. For example, with $D_{\max} = 4$, a client can access at most 12 two-hop candidates, corresponding to at most 24.5% of the population at $N = 50$, 12.1% at $N = 100$, and 1.2% at $N = 1000$. This formalizes a locality-coverage tension: bounded degree controls communication, but the fraction of the population visible through two-hop discovery vanishes as N grows. Increasing degree expands the search frontier but also increases communication, making population size and degree budget distinct scaling axes.

Mixing and disagreement. For symmetric Metropolis–Hastings mixing $P_t = P(G_t)$, let $J = \frac{1}{N} \mathbf{1}\mathbf{1}^\top$ denote global averaging and define

$$\rho_t = \|P_t - J\|_2.$$

Then one communication step satisfies

$$\|(I - J)P_t X\|_F \leq \rho_t \|(I - J)X\|_F, \quad (4)$$

so ρ_t directly controls how quickly model disagreement contracts: smaller ρ_t implies faster mixing [1, 2, 9, 12]. Under non-IID data, local optimization continually reintroduces disagreement, making the learning dynamics a balance between local drift and network mixing.

This dependence becomes explicit for a degree-two Ring, whose mixing eigenvalues are

$$\mu_k = \frac{1 + 2 \cos(2\pi k/N)}{3}, \quad 1 - \mu_1 = \frac{2}{3} \left(1 - \cos \frac{2\pi}{N}\right) = \Theta(N^{-2}). \quad (5)$$

Intuitively, information must travel around an increasingly long cycle, so local updates are averaged across the population progressively more slowly. Hence, as N grows, the Ring spectral gap vanishes quadratically and disagreement contracts increasingly slowly. The Ring therefore provides a concrete population-dependent mixing failure mode. Static Random offers a contrasting sparse regime with approximately constant local degree but without the deterministic cycle bottleneck.

3 Controlled Population and Degree Scaling

We use CIFAR-10 [5] with class-wise Dirichlet heterogeneity $\alpha = 0.3$, $N \in \{10, 50, 100, 200\}$, and seeds $\{42, 43, 44\}$. Training runs for 300 communication rounds with one local epoch per round, SGD with learning rate 0.05, and batch size 32. Evaluation and LFHE topology updates occur every five rounds. We report means and sample SD; further details appear in Appendix B.

We compare **Ring**, a fixed cycle; **Static Random**, a fixed connected sparse graph; and **LFHE**. Static Random and LFHE share seed-matched connected Erdős–Rényi initializations with expected degree four; all methods use degree-aware Metropolis–Hastings mixing.

Data and degree regimes. Under *fixed-total*, the 50,000 CIFAR-10 training examples are partitioned across the population, so per-client data decreases with N . Under *fixed-per-client*, each client instead receives a local dataset of 500 sampled indices, keeping local dataset size constant as the population grows. Full sampling semantics are given in Appendix B.

LFHE uses either a fixed online threshold $D_{\max} = 4$ or the population-dependent schedule

$$D_{\max} = \max(2, \lfloor 2 \ln N \rfloor) = \{4, 7, 9, 10\}.$$

The fixed-threshold setting tests population growth under approximately constant local communication capacity; the scaled-threshold setting measures the benefit and cost of increasing that capacity with population.

Model disagreement and cumulative directed model transmissions are

$$\mathcal{D}_t = \frac{1}{N} \sum_{i=1}^N \left\| \theta_{i,t} - \frac{1}{N} \sum_j \theta_{j,t} \right\|_2^2, \quad M(T) = 2 \sum_{t < T} |E_t|. \quad (6)$$

Communication accounting includes directed model exchange; topology-control traffic and wall-clock latency are not included in this metric.

4 What Drives Population Scaling?

Data allocation changes the scaling regime. With fixed-total data, fixed- $D_{\max}$ LFHE drops from 74.65% to 68.64% over $N = 50 \rightarrow 100$ and from 68.64% to 60.51% over $N = 100 \rightarrow 200$, losses of 6.01 and 8.13 points. Under fixed-per-client training, the corresponding losses are 1.71 points (70.52% $\rightarrow$ 68.81%) and 1.97 points (68.81% $\rightarrow$ 66.84%). Preserving local dataset size therefore reduces the apparent penalties by 4.30 and 6.16 points, respectively.

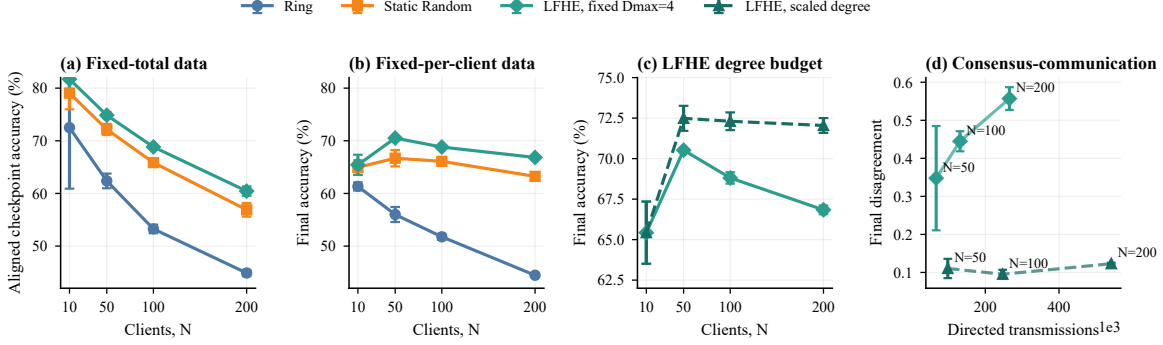


Figure 2: Controlled scaling on CIFAR-10. (a) Fixed-total population scaling; (b) fixed-per-client scaling with $D_{\max} = 4$; (c) LFHE under fixed and population-scaled degree thresholds; (d) disagreement versus realized communication. Panel (a) uses the aligned cross-method checkpoint; the remaining panels report final endpoints. Error bars show sample SD over seeds 42–44.

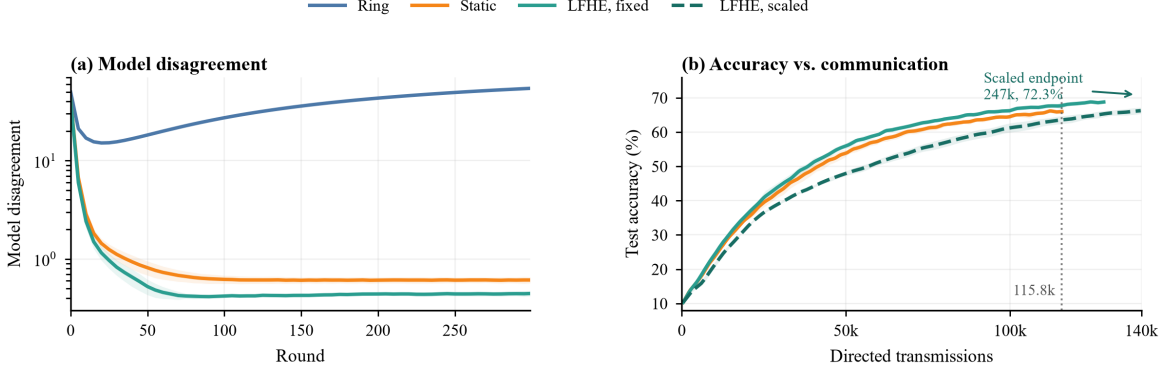


Figure 3: Dynamics at $N = 100$ under fixed-per-client training. (a) Ring enters a high-disagreement regime, while Static Random and fixed- $D_{\max}$ LFHE remain near consensus. (b) Communication-normalized accuracy: fixed- $D_{\max}$ LFHE leads within the shared budget, while scaled-threshold LFHE reaches a higher endpoint at greater cost.

Residual scaling depends on communication structure. Under fixed-per-client training, Ring falls from 61.34% to 44.46% over $N = 10 \rightarrow 200$, while Static Random remains comparatively stable (64.95% $\rightarrow$ 63.24%). Fixed- $D_{\max}$ LFHE reaches 66.84% at $N = 200$, 3.60 points above Static Random with approximately 9.7% more model transmissions. Disagreement trajectories distinguish the same regimes: Ring moves toward high disagreement, whereas Static Random and LFHE remain near consensus (Figure 3a); topology trajectories are reported in Appendix E.

Communication capacity sets a second scaling frontier. Increasing LFHE’s degree threshold raises accuracy from 70.52% to 72.49% at $N = 50$, from 68.81% to 72.31% at $N = 100$, and from 66.84% to 72.04% at $N = 200$, while model transmissions increase by 47.1%, 88.1%, and 104.1%, respectively (Appendix F). At a common 115.8k-transmission budget, fixed- $D_{\max}$ LFHE reaches 67.77% versus 65.98% for Static Random, whereas scaled-threshold LFHE reaches its higher endpoint only after approximately 247k transmissions (Figure 3b). Additional degree therefore extends the attainable learning regime at increasing communication cost.

5 Discussion and Conclusion

Two resource effects shape decentralized scaling. First, **data allocation**: preserving per-client data reduces LFHE’s losses from 6.01 to 1.71 points over $N = 50 \rightarrow 100$ and from 8.13 to 1.97 over $N = 100 \rightarrow 200$, revealing different behavior across structures. Ring deteriorates, Static Random remains comparatively stable, and LFHE maintains higher accuracy with low disagreement.

The second effect is **communication capacity**. Increasing LFHE’s degree threshold improves mixing and raises the achievable endpoint, but the benefit comes with rapidly increasing model exchange. The fixed-threshold results show that LFHE retains a performance advantage over Static Random even when their realized communication is close, while the scaled-threshold results expose how additional degree can trade communication for accuracy.

Together, these findings suggest a broader view of decentralized scaling. Population size is not an isolated systems variable: its effect depends on how data, topology, and communication resources scale with it. For the tested finite-population regime, preserving local data substantially reduces the apparent population penalty, topology determines the remaining consensus pressure, and additional degree determines how far that pressure can be reduced. Scaling studies should therefore report these resources jointly rather than summarize behavior through client count and endpoint accuracy alone.

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A Implementation-Faithful LFHE

For the controlled-scaling CIFAR-10 experiments, LFHE uses a 10-dimensional summary of the final classifier weight matrix as the client representation. Let $W_i^t \in \mathbb{R}^{10 \times 256}$ denote client i 's final classifier weight matrix. The implemented representation is

$$z_i^t = \frac{1}{256} W_i^t \mathbf{1}_{256},$$

obtained by averaging each output class's 256 incoming weights. Its local terms are

$$C_i(G, t) = \sum_{j \in \mathcal{N}_i(G)} \|z_i^t - z_j^t\|_2^2, \quad (7)$$

$$D_i(G, t) = 1 - \cos \left(z_i^t, \frac{1}{|\mathcal{N}_i(G)|} \sum_{j \in \mathcal{N}_i(G)} z_j^t \right), \quad (8)$$

with

$$f_i(G, t) = (1 - \beta_t) C_i(G, t) + \beta_t D_i(G, t) - 0.1 \frac{d_i(G)}{D_{\max}}, \quad \beta_t = e^{-0.01t}.$$

The structural term is representation-dependent and is not a direct estimator of algebraic connectivity. At each topology epoch, initiators are processed once in a fixed sequential order. Each initiator samples

$$h \sim \text{Unif}(\mathcal{N}_i), \quad k \in \mathcal{N}_h \setminus (\mathcal{N}_i \cup \{i\}),$$

and evaluates that FoF candidate against its current graph state. A simple addition is available when the relevant online degree conditions are satisfied; otherwise, LFHE evaluates feasible one-edge replacements. Each initiator commits at most one accepted add-or-swap operation before processing moves to the next client, which then observes the already updated graph. The implementation therefore uses sequential rather than concurrent topology commits.

The threshold $D_{\max}$ regulates online edge acquisition. Because the connected Erdős–Rényi initializer is specified by expected degree, some nodes may initially exceed the threshold; these degrees are preserved unless subsequently changed by topology updates. Consequently, fixed- $D_{\max} = 4$ runs have mean degree near 4.4, while endpoint maximum degree can exceed four.

B Experimental Details

Controlled scaling uses CIFAR-10 [5], class-wise Dirichlet $\alpha = 0.3$, $N \in \{10, 50, 100, 200\}$, seeds $\{42, 43, 44\}$, 300 communication rounds, one local epoch per round, SGD with learning rate 0.05, batch size 32, evaluation every five rounds, and LFHE topology updates every five rounds.

All methods use the same CIFAR-10 convolutional model: two convolutional stages with 32 and 64 channels, batch normalization and max pooling, followed by a 256-dimensional fully connected hidden representation, dropout 0.3, and a 10-way classifier. In the controlled-scaling runs, LFHE uses the 10-dimensional class-wise mean of the final classifier weight matrix as its topology representation signal. The separate matched-FoF diagnostic uses the complete flattened 10×256 final classifier weight matrix. The architecture, preprocessing pipeline, and optimizer configuration are held identical across Ring, Static Random, and LFHE. The controlled conditions vary data allocation and communication topology; because training uses one local epoch, the data regime also determines the per-round local SGD workload.

Ring uses a cycle. Static Random and LFHE use seed-matched connected Erdős–Rényi initializations with expected degree four. For neighboring clients,

$$a_{ij} = \frac{1}{1 + \max(d_i, d_j)}, \quad a_{ii} = 1 - \sum_{j \in \mathcal{N}_i} a_{ij}.$$

Under fixed-total training, all 50,000 CIFAR-10 training examples are partitioned across the population. Under fixed-per-client training, each client draws 500 local-dataset indices only from its own Dirichlet pool and reuses the resulting local dataset throughout training. This holds the nominal number of local training entries

fixed at 500 per client. Sampling is without replacement when the client’s pool contains at least 500 indices and with replacement otherwise; repeated indices therefore do not introduce data from another client’s pool.

The two LFHE threshold regimes are

$$\text{fixed: } D_{\max} = 4, \quad \text{scaled: } D_{\max} = \max(2, \lfloor 2 \ln N \rfloor) = \{4, 7, 9, 10\}.$$

The controlled fixed-threshold runs store exact graph snapshots every five communication rounds together with the final topology. Algebraic connectivity is computed from the unweighted combinatorial Laplacian $L = D - A$ of these exact edge lists. Historical scaled-threshold runs without evolving adjacency snapshots are not used to construct spectral trajectories.

Model disagreement is

$$\mathcal{D}_t = \frac{1}{N} \sum_{i=1}^N \|\theta_{i,t} - \bar{\theta}_t\|_2^2, \quad \bar{\theta}_t = \frac{1}{N} \sum_i \theta_{i,t}.$$

All uncertainty values reported for the controlled study are sample SD over the three paired seeds.

Table 1: Matched-FoF diagnostic at $N = 30$, $\alpha = 0.1$, over seeds 42–44. Runs use 300 rounds, topology updates every five rounds, $D_{\max} = 6$, and a budget of six proposals per topology update. Adaptive variants share initialization, candidate generation, update frequency, and proposal budget; only the local score changes. $\Delta\lambda_2$ is measured relative to Static at the final endpoint. Ops./update is the system-wide number of accepted topology operations per update, averaged over updates and seeds.

Method	Final λ_2	$\Delta\lambda_2$	Final Acc.	Final Div.	Ops./update
Static	0.592	0.000	0.6675	0.781	0.000
Similarity-only	0.578	-0.014	0.6704	0.736	0.183
Exploration-only	1.038	0.447	0.7356	0.208	3.406
Structural-only	2.306	1.715	0.7508	0.136	1.111
LFHE	2.247	1.655	0.7482	0.135	1.333

Exploration-only accepts substantially more topology operations per update than Structural-only or LFHE yet reaches lower algebraic connectivity and lower accuracy. Operation frequency alone therefore does not explain the resulting trajectory; changing the local scoring rule materially changes the graph-model regime produced by the same FoF update process.

C Controlled Scaling Results

Table 2: Final fixed-per-client accuracy (% , mean $\pm$ sample SD over seeds 42–44).

Method	$N = 10$	$N = 50$	$N = 100$	$N = 200$
Ring	61.34 $\pm$ 0.77	56.00 $\pm$ 1.43	51.77 $\pm$ 0.57	44.46 $\pm$ 0.27
Static Random	64.95 $\pm$ 1.40	66.69 $\pm$ 1.56	66.10 $\pm$ 0.43	63.24 $\pm$ 0.50
LFHE, fixed ($D_{\max} = 4$)	65.43 $\pm$ 1.92	70.52 $\pm$ 0.07	68.81 $\pm$ 0.35	66.84 $\pm$ 0.27
LFHE, scaled threshold	65.43 $\pm$ 1.92	72.49 $\pm$ 0.77	72.31 $\pm$ 0.55	72.04 $\pm$ 0.46

The 0.07 sample SD for fixed- $D_{\max}$ LFHE at $N = 50$ is computed directly across the three completed seeds.

Table 3: Final fixed- $D_{\max} = 4$ LFHE endpoints at $N \in \{50, 100, 200\}$ (mean $\pm$ sample SD).

Regime	Metric	$N = 50$	$N = 100$	$N = 200$
Fixed-total	Accuracy (%)	74.65 $\pm$ 1.89	68.64 $\pm$ 0.59	60.51 $\pm$ 0.96
	Disagreement	0.474 $\pm$ 0.116	0.354 $\pm$ 0.004	0.257 $\pm$ 0.029
	λ_2	0.603 $\pm$ 0.142	0.465 $\pm$ 0.124	0.523 $\pm$ 0.063
Fixed-per-client	Accuracy (%)	70.52 $\pm$ 0.07	68.81 $\pm$ 0.35	66.84 $\pm$ 0.27
	Disagreement	0.348 $\pm$ 0.137	0.445 $\pm$ 0.027	0.557 $\pm$ 0.030
	λ_2	0.550 $\pm$ 0.217	0.426 $\pm$ 0.076	0.497 $\pm$ 0.058

Table 4: Final fixed-per-client model disagreement.

Method	$N = 10$	$N = 50$	$N = 100$	$N = 200$
Ring	0.439	27.482	54.391	67.414
Static Random	0.129	0.578	0.611	0.803
LFHE, fixed ($D_{\max} = 4$)	0.180	0.348	0.445	0.557
LFHE, scaled threshold	0.180	0.110	0.095	0.123

D Communication Accounting

Table 5: LFHE cumulative directed model transmissions under fixed-per-client training (mean over seeds 42–44).

Threshold regime	$N = 50$	$N = 100$	$N = 200$
Fixed ($D_{\max} = 4$)	66,710	131,419	265,519
Scaled threshold	98,160	247,254	541,831
Increase	47.1%	88.1%	104.1%

Table 6: Fixed-per-client communication endpoints at $N = 100$ and $N = 200$. Counts include directed model transmissions and exclude separately unlogged topology-control traffic.

Method	$N = 100$	$N = 200$
Ring	60,000	120,000
Static Random	120,600	242,000
LFHE, fixed ($D_{\max} = 4$)	131,419	265,519
LFHE, scaled threshold	247,254	541,831

At $N = 100$ and $N = 200$, fixed-threshold LFHE uses approximately 9% and 9.7% more model transmissions than Static Random, respectively. Scaling the LFHE threshold from four to nine at $N = 100$ increases communication by 88.1%, while scaling it from four to ten at $N = 200$ increases communication by 104.1%.

E Graph–Model Dynamics Under a Fixed Degree Budget

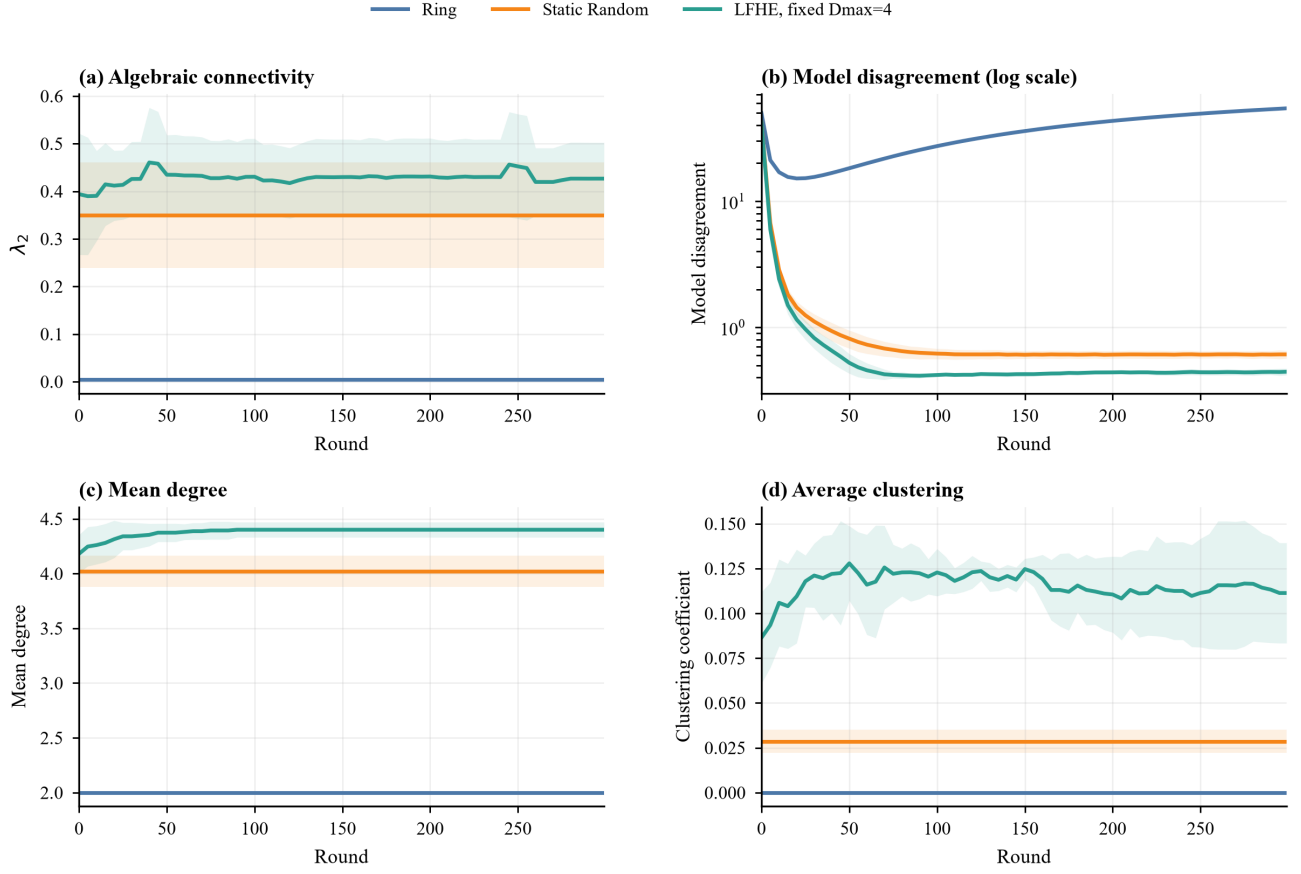


Figure 4: Graph–model dynamics at $N = 100$ under fixed-per-client training with $D_{\max} = 4$. LFHE maintains stronger algebraic connectivity than Ring while mean degree remains near 4.4, and its disagreement converges to the low-disagreement regime shared with Static Random. Curves show means over seeds 42–44; shading is sample SD.

At $N = 100$, LFHE’s algebraic connectivity changes from 0.394 to 0.426 while its mean degree remains near 4.4. Static Random remains near 0.35, whereas the Ring has substantially weaker algebraic connectivity. At the same time, LFHE’s model disagreement contracts from a large initial value to 0.445, Static Random stabilizes near 0.6, and Ring enters a substantially higher-disagreement regime.

Structural and optimization changes are concentrated in the early part of training, after which both topology and disagreement become comparatively stable. The exact trajectories show that topology evolution and consensus formation occur on related but non-identical time scales, reinforcing the view of LFHE as a coupled graph–model process rather than a single spectral optimization step.

F Degree-Budget Diagnostic

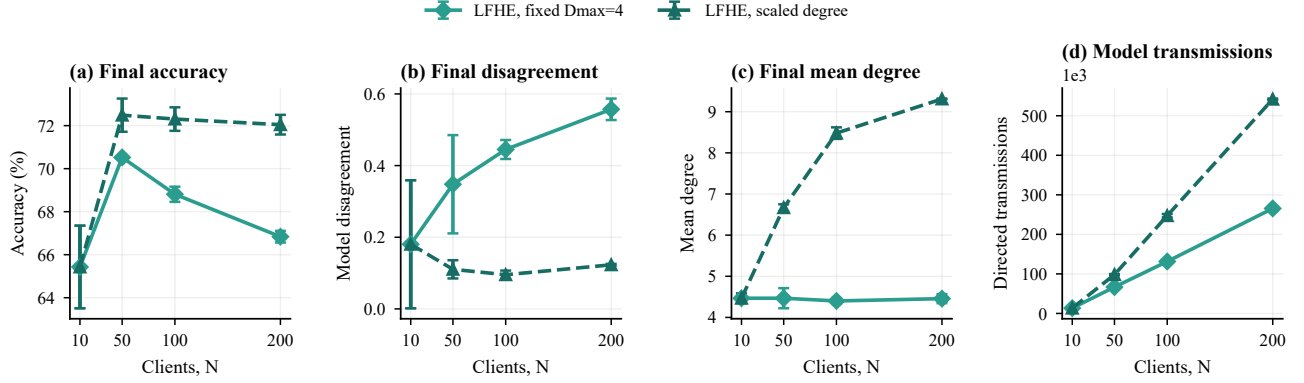


Figure 5: LFHE degree-budget sensitivity under fixed-per-client training. Increasing the online threshold produces higher endpoint accuracy and lower disagreement, together with higher realized degree and communication.

At $N = 50$, changing $D_{\max}$ from 4 to 7 raises accuracy from 70.52% to 72.49%, reduces disagreement from 0.348 to 0.110, and increases transmissions from 66,710 to 98,160. At $N = 100$, changing $D_{\max}$ from 4 to 9 raises accuracy from 68.81% to 72.31%, reduces disagreement from 0.445 to 0.095, and increases transmissions from 131,419 to 247,254. At $N = 200$, changing $D_{\max}$ from 4 to 10 raises accuracy from 66.84% to 72.04%, reduces disagreement from 0.557 to 0.123, and increases transmissions from 265,519 to 541,831.

This comparison quantifies LFHE’s sensitivity to additional degree capacity. The corresponding communication-normalized behavior is reported in Appendix G.

G Communication-Normalized Learning

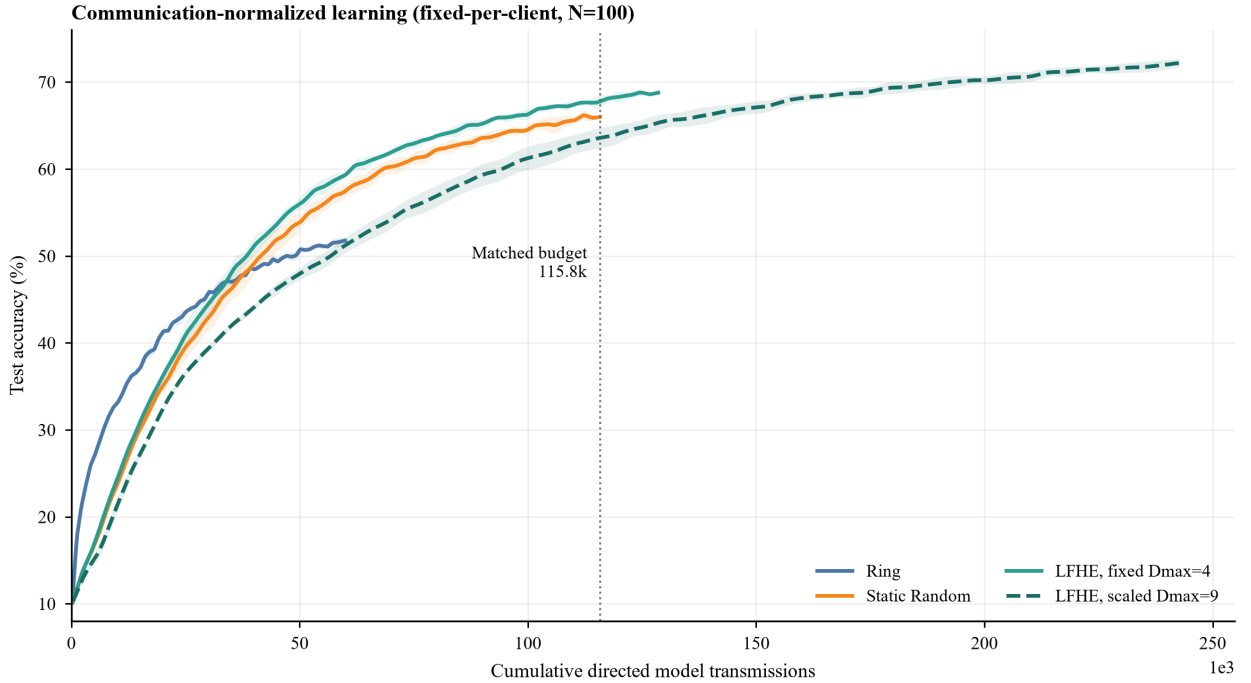


Figure 6: Accuracy versus cumulative directed model transmissions at $N = 100$ under fixed-per-client training. Scaled-threshold LFHE attains the highest endpoint after extending substantially beyond the fixed-threshold communication range.

At a common budget of 115.8k transmissions, Static Random, fixed- $D_{\max}$ LFHE, and scaled-threshold LFHE achieve 65.98%, 67.77%, and 63.58%, respectively. The transmissions required to first reach 65% accuracy are approximately 106.3k, 88.6k, and 130.7k. Fixed-threshold LFHE therefore reaches stronger learning within the shared communication range, whereas scaled-threshold LFHE trades a larger total budget for a higher eventual endpoint.

H Scope and Extensions

The controlled study focuses on CIFAR-10, populations up to $N = 200$, and three paired seeds, with communication measured through directed model transmissions. Within this setting, the experiments characterize how data allocation, mixing structure, local search visibility, and communication capacity shape the observed scaling regime. LFHE uses final classifier weights as its representation signal throughout; evaluating alternative representation layers or learned signals would further characterize the sensitivity of the topology process.

Extending the analysis to larger populations and broader learning tasks would test whether the same graph-model regimes persist beyond the finite-population setting studied here. An equally dense fixed-graph comparison would further separate additional connectivity from topology adaptation when degree grows, while concurrent topology updates would extend the present sequential protocol toward asynchronous decentralized execution. Comparisons with additional adaptive-topology processes such as PENS and Morph are also natural extensions under the same controlled data and communication regimes.