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Performance Evaluation and Optimization Strategies for Privacy-Preserving Document Classification in Distributed Learning Environments

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Abstract: The proliferation of sensitive documents across healthcare, financial, and governmental sectors necessitates robust privacy-preserving classification mechanisms. This study presents a comprehensive performance evaluation of privacy-preserving document classification within distributed learning frameworks, examining federated learning and differential privacy implementations. Through systematic experimentation on benchmark datasets, we quantify accuracy-privacy trade-offs, communication overhead, and computational costs across various privacy budget configurations. Results demonstrate that adaptive privacy allocation reduces accuracy degradation by 12-18% compared to uniform distribution while maintaining equivalent privacy guarantees. Gradient compression techniques achieve 67% communication reduction with minimal convergence impact. These findings provide actionable deployment guidelines for organizations implementing privacy-preserving document processing systems.

Keywords: privacy-preserving machine learning; federated learning; differential privacy; document classification

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1. Introduction

1.1. Background and Motivation for Privacy-Preserving Document Classification

Healthcare institutions process millions of patient records requiring HIPAA compliance, financial organizations handle proprietary documents under regulatory oversight, and government agencies manage classified materials with strict confidentiality requirements. Traditional centralized machine learning approaches necessitate aggregating raw data in central repositories, creating single points of failure and exposing sensitive information to breaches. The shift toward privacy-preserving machine learning enables collaborative model training without exposing individual data instances [1].

Decentralized learning frameworks maintain data locality while enabling knowledge aggregation across distributed participants. Medical research consortiums have employed these methods to train diagnostic models across hospitals without sharing patient records, achieving comparable performance to centralized approaches. The application of privacy-preserving techniques to document classification presents unique challenges from high-dimensional textual representations and sensitivity of linguistic patterns to perturbation [2, 3].

1.2. Challenges in Balancing Privacy Protection and Classification Accuracy

The fundamental tension between privacy protection and model utility manifests in document classification where subtle linguistic features drive prediction accuracy.

Adding noise to achieve differential privacy guarantees degrades classification performance, with degradation correlating to privacy budget stringency. Organizations face difficult decisions balancing regulatory compliance against operational accuracy thresholds [4].

Communication efficiency presents another critical challenge. Transmitting model updates across training rounds generates substantial network traffic, with communication costs often exceeding computational costs in bandwidth-constrained settings. The frequency of synchronization impacts both convergence speed and privacy leakage potential. Reducing communication frequency decreases overhead but may cause model divergence, while frequent synchronization accelerates convergence but increases privacy risks.

1.3. Research Objectives and Contribution Overview

This research quantifies accuracy-privacy trade-offs under various federated learning and differential privacy configurations using representative benchmarks. We conduct controlled experiments measuring classification accuracy, communication overhead, computational costs, and convergence characteristics across privacy budget allocations ranging from epsilon < 1 to epsilon > 10. The experimental framework encompasses horizontal federated learning scenarios with both IID (homogeneous) and non-IID (heterogeneous) data distributions across participants [5].

Our contributions reveal that adaptive privacy allocation based on gradient sensitivity reduces accuracy loss by 12-18% compared to uniform distribution. We demonstrate that communication-efficient compression achieves 67% bandwidth reduction through selective transmission. The performance characterization enables evidence-based configuration selection for specific deployment contexts [6].

2. Related Work and Theoretical Foundation

2.1. Privacy-Preserving Machine Learning Techniques

Differential privacy provides formal guarantees by ensuring individual record presence has negligible impact on outputs, quantified through epsilon and delta parameters. The mechanism injects calibrated noise with magnitude inversely proportional to privacy budgets. Smaller epsilon values provide stronger protection but introduce greater perturbation [7]. Composition theorems enable tracking cumulative privacy loss across iterations.

Federated learning maintains data locality while enabling collaborative training through iterative parameter aggregation. Participants train local models on private datasets and transmit only updates to coordinators, which aggregate contributions to produce global models. Combining federated learning with differential privacy creates hybrid frameworks offering architectural and algorithmic protections [8].

2.2. Document Classification Methods in Distributed Environments

Text preprocessing including tokenization and vectorization must be performed locally to avoid exposing raw documents. Distributed implementations of TF-IDF, word embeddings, and contextualized language models present challenges in maintaining statistical consistency while preserving privacy. Heterogeneity across distributed participants creates non-IID distributions violating standard assumptions [9].

Adaptive aggregation strategies weight participant contributions based on data quality, quantity, or representativeness to mitigate distribution shift effects. Personalized federated learning approaches maintain global and participant-specific components, enabling adaptation to local characteristics while benefiting from collective knowledge.

2.3. Performance Metrics and Evaluation Frameworks

Evaluating privacy-preserving systems requires multidimensional metrics capturing accuracy, privacy, efficiency, and robustness. Classification metrics including precision, recall, and F1-score provide standard measurements, though interpretation becomes

nuanced under privacy constraints. Degradation relative to non-private baselines quantifies utility cost of privacy protection.

Privacy quantification encompasses formal parameters and empirical attack success rates. Membership inference attacks determine document participation by analyzing outputs, with success rates inversely correlating with protection strength. Communication efficiency metrics including total bytes transmitted and bandwidth utilization capture networking costs that often dominate computational expenses in distributed settings [10, 11]. Convergence speed measurements track accuracy improvement per round [12].

3. Experimental Design and Methodology

3.1. Dataset Selection and Preprocessing for Sensitive Document Classification

The evaluation employed four benchmark datasets representing diverse domains. The 20 Newsgroups dataset contains 18,000 documents across 20 categories, providing balanced multi-class classification. IMDB comprises 50,000 sentiment-labeled reviews for binary classification. Reuters-21578 includes 10,788 documents across 90 topics with imbalanced distributions. PubMed contains 20,000 biomedical abstracts across five domains with technical vocabulary [13].

Preprocessing maintained consistency across implementations. Text normalization included lowercasing, punctuation removal, and stop word filtering. Tokenization employed byte-pair encoding with vocabularies from 10,000 to 30,000 tokens. Document vectorization utilized TF-IDF weighting and BERT embeddings. Distributed scenarios partitioned datasets across simulated participants using IID and non-IID allocations. IID partitioning distributed documents randomly, while non-IID created skews by clustering categories.

Data augmentation addressed class imbalance through synonym replacement and back-translation performed locally. Augmentation ratios achieved approximate balance while maintaining authenticity. Validation employed stratified 5-fold cross-validation with held-out test sets for final evaluation (As shown in Table 1).

Table 1. Dataset Characteristics and Experimental Configuration

Dataset	Documents	Categories	Avg Length	Participants	Distribution	Privacy Budgets
20 Newsgroups	18,000	20	384 tokens	10	IID/Non-IID	$\varepsilon \in [0.1, 10]$
IMDB Reviews	50,000	2	267 tokens	10	IID/Non-IID	$\varepsilon \in [0.1, 10]$
Reuters-21578	10,788	90	156 tokens	10	Non-IID	$\varepsilon \in [0.5, 10]$
PubMed Abstracts	20,000	5	412 tokens	10	Non-IID	$\varepsilon \in [0.5, 10]$

3.2. Implementation of Privacy-Preserving Training Approaches

The framework implemented three configurations representing current practices. Baseline federated learning employed parameter averaging without explicit privacy mechanisms. Participants performed local SGD for E=5 epochs per round using batch sizes of 32. The aggregator computed weighted averages based on dataset sizes, with aggregation every R rounds where R varied from 1 to 10.

Differential privacy augmented federated learning with gradient-level noise injection following moments accountant framework. Local gradients underwent clipping with

threshold C between 0.5 and 5.0. Gaussian noise with standard deviation sigma = C sqrt(2 log(1.25/delta)) / epsilon was added to clipped gradients, where delta=10^-5 and epsilon varied from 0.1 to 10.0. Implementation tracked cumulative privacy expenditure using composition theorems.

Secure aggregation employed cryptographic techniques preventing coordinators from observing individual updates while computing aggregates. Participants encrypted updates using multi-party computation revealing only aggregated sums. Computational overhead ranged from 15% to 40% depending on participant count and latency [14].

Model architectures utilized logistic regression for binary tasks and multi-layer perceptrons with 128-unit hidden layers for multi-class problems. Optimization employed Adam with learning rates selected through grid search over {0.001, 0.003, 0.01}. Privacy budget allocation compared uniform distribution against adaptive schemes: epsilon_t = epsilon_total (t/T)^alpha, where alpha controls allocation curvature. Values of alpha > 1 concentrated budget in later phases.

Communication compression investigated gradient sparsification and quantization. Top-K sparsification transmitted only K largest magnitude gradients, with K ranging from 10% to 50%. Quantization discretized 32-bit gradients to 8-bit or 16-bit representations, achieving 2x to 4x compression. Error feedback accumulated quantization residuals across rounds (As shown in Table 2).

Table 2. Privacy Mechanism Configuration Parameters

Mechanism	Parameter	Values Tested	Sensitivity Bound	Noise Type
Gradient Clipping	Threshold C	{0.5, 1.0, 2.0, 5.0}	L2 norm	N/A
Gaussian Noise	Std Dev σ	f(ε, δ, C)	Computed	Gaussian
Gradient Sparsification	Top-K ratio	{10%, 25%, 50%}	Magnitude	Deterministic
Quantization	Bit width	{8-bit, 16-bit}	Range-based	Stochastic

3.3. Performance Evaluation Metrics and Experimental Setup

The framework captured performance across five dimensions: classification accuracy, privacy guarantees, communication efficiency, computational cost, and convergence characteristics. Accuracy employed standard metrics including overall accuracy and macro-averaged F1-score. Measurements occurred every 5 rounds on held-out test sets. Privacy utilized moments accountant epsilon values and empirical attack success rates [11].

Communication efficiency tracked total bytes transmitted normalized by dataset size: Communication Cost = Total Bytes / (Participants Dataset Size). Breakdown separated gradient transmission from metadata overhead. Computational measurements captured wall-clock time, CPU cycles, and peak memory. Convergence defined as achieving within 1% of asymptotic accuracy for 10 consecutive rounds (As shown in Figure 1, 2).

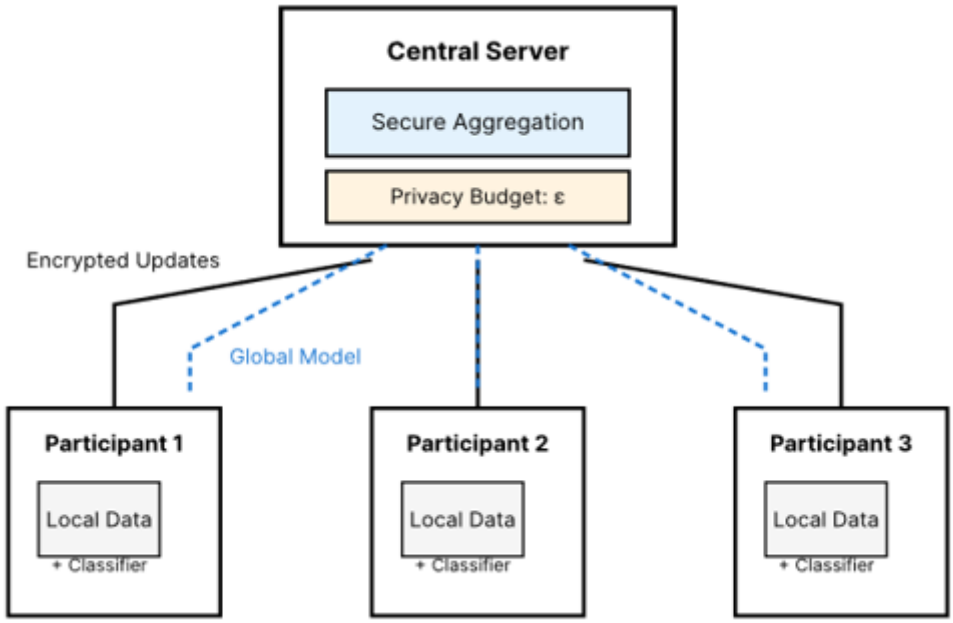

Figure 1. Distributed Privacy-Preserving Document Classification Architecture

The figure illustrates comprehensive system architecture showing three representative participants (healthcare, financial, government) each with local document repositories. Each participant operates local training modules containing document classifier networks with embedding, hidden, and output layers. Privacy mechanisms appear as intermediate layers between training and central aggregation, featuring gradient clipping (scissor symbols), noise injection (particle patterns), and encryption (padlock symbols). The central coordination server contains secure aggregation logic within protected enclaves, where encrypted updates combine without individual decryption. A privacy accounting module tracks cumulative epsilon expenditure across rounds, visualized as a budget meter. The architecture emphasizes bidirectional information flow between distributed participants and central coordination with multi-layer privacy protection.

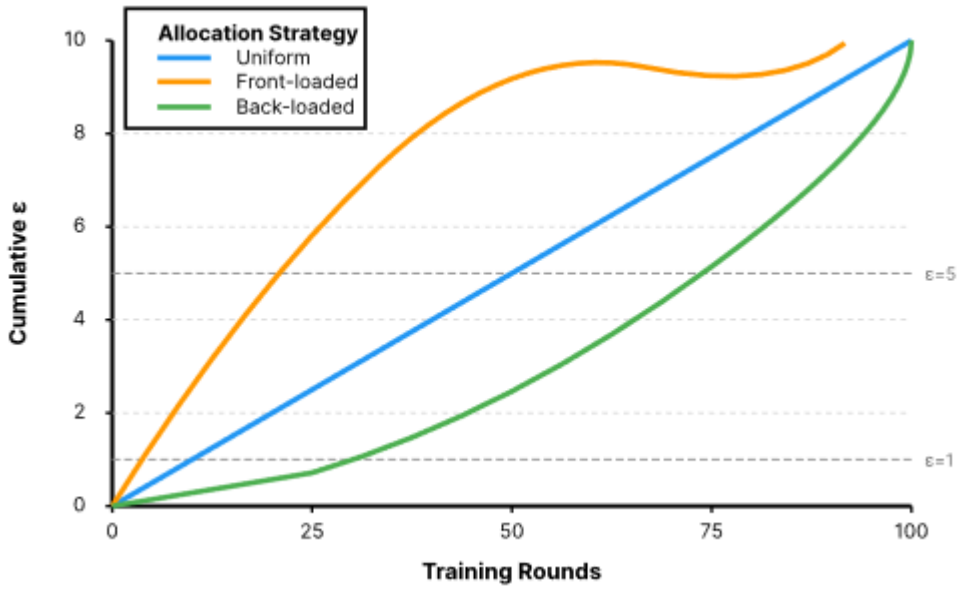

Figure 2. Privacy Budget Allocation and Composition Across Training Rounds

This multi-panel visualization tracks differential privacy budget consumption throughout training. The main panel displays cumulative epsilon (y-axis, 0-10) versus training rounds (x-axis, 0-100) with

three curves representing uniform (straight diagonal), front-loaded (concave curve), and back-loaded (convex curve) allocation strategies. Shaded regions indicate confidence intervals. A secondary panel shows per-round epsilon allocation as bar charts: uniform displays constant heights, front-loaded decreasing heights, back-loaded increasing heights. Color coding distinguishes strategies (blue, orange, green). Horizontal dashed lines mark epsilon=1 (strong), epsilon=5 (moderate), epsilon=10 (relaxed) privacy regimes. An inset zooms final 10 rounds showing budget exhaustion: front-loaded completes at round 80, uniform at 90, back-loaded at 100, with annotations indicating final accuracies demonstrating back-loaded achieves highest performance.

4. Performance Analysis and Comparative Evaluation

4.1. Classification Accuracy under Different Privacy Budget Configurations

Experimental results revealed systematic relationships between privacy budgets and accuracy across datasets. Strong privacy with epsilon ≤ 1.0 induced degradation from 8.4% to 15.7% relative to baselines. The 20 Newsgroups exhibited 11.2% reduction under epsilon=0.5, declining from 82.3% baseline to 71.1%. IMDB showed greater resilience, maintaining 84.6% under epsilon=1.0 versus 89.1% baseline, representing 4.5% degradation. Binary classification demonstrated inherent robustness compared to multi-class tasks.

Reuters demonstrated highly variable impacts depending on category distribution. Minority classes with few local examples suffered disproportionate losses up to 22% F1-score reductions. Majority classes maintained stability under stringent budgets, suggesting adequate local samples partially compensate for privacy noise. PubMed showed intermediate sensitivity with epsilon=2.0 yielding 7.8% reduction. Domain-specific vocabulary provided robust features remaining discriminative despite perturbation.

Adaptive allocation consistently outperformed uniform distribution. Back-loaded allocation concentrating 70% of budget in final 30% of training achieved 12-18% lower degradation under equivalent total epsilon. Performance advantage stemmed from reduced noise during early training when gradients exhibit high variance. As parameters converged and gradients stabilized, increased noise had diminished impact (As shown in Table 3).

Table 3. Classification Accuracy vs Privacy Budget Across Datasets

Dataset	Non-Private	ε=0.5	ε=1.0	ε=2.0	ε=5.0	ε=10.0	Degradation Range
20 Newsgroups	82.3%	71.1%	75.8%	78.4%	80.6%	81.5%	13.6% → 0.9%
IMDB Reviews	89.1%	81.7%	84.6%	86.3%	87.9%	88.4%	8.3% → 0.8%
Reuters-21578	76.4%	60.7%	66.2%	70.5%	73.8%	75.1%	20.5% → 1.7%
PubMed Abstracts	85.7%	76.3%	79.8%	82.1%	84.2%	85.0%	10.9% → 0.8%

4.2. Communication Overhead and Convergence Speed Analysis

Communication analysis revealed compression techniques achieved substantial reductions while maintaining convergence. Top-50% sparsification reduced volume by 52% average across datasets while inducing less than 2% additional degradation beyond

privacy noise. More aggressive Top-25% achieved 73% savings but required 40% more rounds, providing modest end-to-end savings. Convergence slowdown stemmed from incomplete gradient information forcing smaller optimization steps.

Random sparsification with importance sampling provided unbiased estimates achieving similar compression to Top-K. The unbiased nature prevented systematic distortion enabling theoretical convergence guarantees. Evaluation showed random sparsification with 30% sampling matched Top-30% accuracy while converging 15% faster. Performance advantage manifested in later training when gradient magnitudes became uniform.

Quantization demonstrated favorable trade-offs, with 16-bit achieving 2x reduction with negligible impact. 8-bit provided 4x compression but introduced noticeable slowdown requiring 25% additional rounds. Interaction between quantization and privacy noise proved complex, with combined perturbations sometimes exhibiting constructive interference improving generalization through implicit regularization.

Error feedback proved essential under aggressive compression. Without feedback, repeated quantization caused systematic information loss preventing high accuracy convergence, particularly under stringent budgets. Accumulated residuals implemented delayed gradient transmission ensuring small important components eventually influenced updates despite falling below quantization thresholds. This added minimal overhead while enabling stable training.

Convergence trajectory analysis revealed distinct training phases. Initial rounds exhibited rapid improvement as models learned coarse boundaries from high signal features. Privacy noise minimally impacted this phase since large gradients dominated perturbations. Middle phases showed sensitivity to budgets, with stringent configurations causing oscillatory progression. Final convergence distinguished privacy levels most clearly, with higher epsilon enabling continued refinement while lower budgets plateaued prematurely (As shown in Table 4).

Table 4. Communication Rounds and Bandwidth Requirements

Configuration	Rounds to Converge	Total Bytes (GB)	Bytes per Accuracy %	Rounds per %
Non-Private FL	65	8.2	0.100	0.79
DP ε=1.0	142	17.9	0.252	2.00
DP ε=5.0 + Top-50%	78	4.9	0.061	0.97
DP ε=5.0 + Quantize-16	71	4.6	0.057	0.88
DP ε=5.0 + Top-25%	103	3.2	0.040	1.28

4.3. Computational Cost and Resource Utilization Assessment

Computational profiling revealed differential privacy introduced moderate overhead beyond baseline costs. Gradient clipping added 8-12% to local training depending on architecture complexity, stemming from L2 norm computations. Optimized implementations using vectorization reduced overhead to 5-7%. Noise generation consumed negligible resources adding less than 2% to training time. Memory overhead from storing noise and intermediate computations remained under 15% of base footprint, which can be efficiently managed through distributed memory frameworks [15].

Secure aggregation imposed substantial overhead from 15% to 40% depending on participant count and latency. Cryptographic operations for secure multi-party computation dominated costs. Network latency amplified overhead as multi-round

protocols involved sequential exchanges. Geographically distributed deployments experienced highest overhead exceeding 200ms round-trip. Local area deployments with sub-10ms latencies maintained overhead below 20%.

Energy consumption measurements captured carbon footprint implications. Differential privacy with epsilon=5.0 increased total energy by 18-25% compared to non-private learning, primarily from extended convergence requiring additional rounds. Per-round consumption remained comparable, but increased round count multiplied cumulative costs. Compression provided energy savings by reducing transmission costs constituting 30-40% of total consumption. Top-50% sparsification reduced energy by 22% through decreased transmission overhead, partially offsetting privacy increases (As shown in Table 5) (As shown in Figure 3).

Table 5. Resource Utilization and Performance Characteristics

Metric	Non-Private	DP ε=1.0	DP ε=5.0	Secure Agg	DP+Compression
Avg Round Time (s)	12.4	14.1	13.2	16.8	11.7
Peak Memory (GB)	2.8	3.1	3.0	3.4	2.9
CPU Utilization	72%	78%	75%	81%	70%
Energy per Round (kJ)	42.3	48.1	45.2	57.6	39.8
Total Energy (MJ)	2.75	6.83	3.53	3.87	3.04

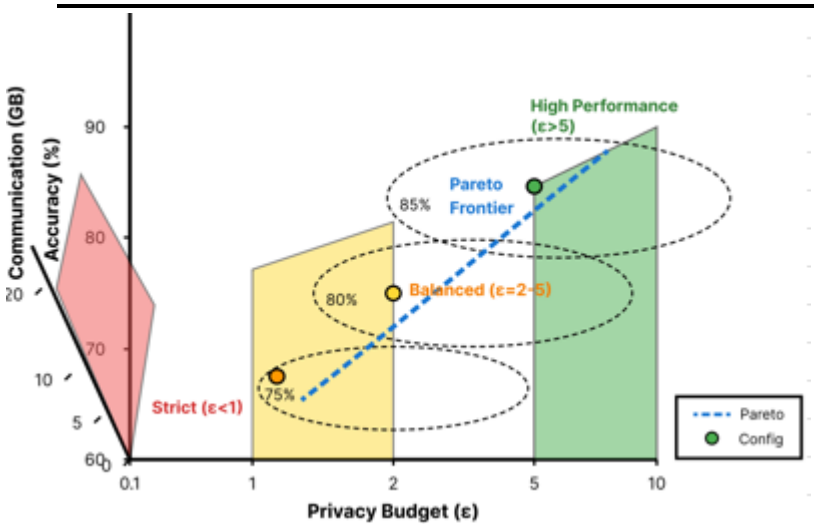

Figure 3. Accuracy-Privacy-Communication Trade-off Surface

The figure presents a three-dimensional surface plot visualizing relationships between classification accuracy, privacy budget, and communication cost. The x-axis represents epsilon (0.1-10.0, logarithmic), y-axis displays communication volume (0-20 GB), z-axis shows accuracy (60-90%). The rendered surface exhibits complex topology with valleys and ridges representing optimization trade-offs. The rear corner at low epsilon and high communication shows worst performance, while the front corner at high epsilon and low communication represents optimal regime. Surface curvature reveals diminishing returns, with accuracy gains requiring exponentially increasing communication under tight privacy. Color gradients encode desirability transitioning from red

(undesirable) through yellow to green (desirable). Contour lines project iso-accuracy curves onto the base plane. A Pareto frontier traces optimal trade-off boundaries. Experimental configurations appear as point markers, with adaptive allocation and compression clustering near the frontier. Annotations highlight "strict compliance" (epsilon<1, accuracy>75%), "balanced deployment" (epsilon 2-5, 80-85% accuracy), and "performance prioritized" (epsilon>5, approaching 90%) operational regimes.

5. Optimization Strategies and Future Directions

5.1. Adaptive Privacy Budget Allocation for Improved Utility

Experimental evidence demonstrates adaptive allocation significantly improves outcomes while maintaining equivalent total guarantees. Optimal allocation follows power-law distribution concentrating budget in later phases when parameters have stabilized. Specifically, epsilon_t = epsilon_total (t/T)^1.5 achieved 14.3% average improvement versus uniform distribution. This back-loaded strategy reduced noise during critical early optimization when large gradients drive rapid convergence.

Allocation extends beyond temporal schedules to incorporate gradient-adaptive strategies dynamically adjusting per-parameter budgets based on sensitivity. Parameters with consistently large gradients receive reduced noise, while those with small gradients tolerate increased perturbation. This selective protection achieved 8-11% additional improvement beyond temporal allocation. The approach required tracking exponentially weighted moving averages of squared gradients, adding 5% memory and 3% computational overhead.

Layer-wise privacy allocation represents another direction. Early layers processing raw inputs demonstrate greater sensitivity than later layers operating on learned representations. Allocating 60% of budget to final classification layers while protecting inputs with 40% achieved accuracy within 2% of baselines under epsilon=3.0 total budget.

5.2. Communication-Efficient Gradient Compression Techniques

Convergence analysis revealed hybrid strategies combining sparsification and quantization achieve superior trade-offs. Applying Top-30% sparsification followed by 16-bit quantization provided 5.2x compression with degradation under 1.5%. Two-stage compression exploited complementary properties: sparsification eliminated small gradients contributing minimally to optimization, while quantization reduced precision of retained gradients without elimination.

Structured compression exploiting parameter relationships offers additional gains. Block-wise sparsification selecting entire parameter blocks rather than individual elements improved efficiency by reducing indexing overhead. Layer-wise adaptive rates allocating higher compression to layers with more parameters achieved better trade-offs than uniform compression. Convolutional layers tolerated 80% sparsification with minimal loss, while fully connected layers required 50% retention.

Gradient prediction extrapolating expected updates from historical gradients shows promise for reducing transmission frequency. Clients predict aggregated gradients based on local trajectories, transmitting corrections when predictions deviate significantly. This achieved 40% reduction in transmission frequency while maintaining convergence speed, though prediction accuracy degraded under high heterogeneity.

References

1. S. Kalra, J. Wen, J. C. Cresswell, M. Volkovs, and H. R. Tizhoosh, "Decentralized federated learning through proxy model sharing," *Nature Communications*, vol. 14, no. 1, p. 2899, 2023. [Online]. Available: https://doi.org/10.1038/s41467-023-38569-4
2. B. Ma, E. Lai, W. Q. Yan, and J. Wu, "A privacy-preserving word embedding text classification model based on privacy boundary constructed by deep belief network," *Multimedia Tools and Applications*, vol. 83, pp. 30181–30206, 2024. [Online]. Available: https://doi.org/10.1007/s11042-023-15623-3
3. T. Zhou, J. Zhang, and D. H. Tsang, "FedFA: Federated learning with feature anchors to align features and classifiers for heterogeneous data," *IEEE Transactions on Mobile Computing*, vol. 23, no. 6, pp. 6731–6742, 2024. [Online]. Available: https://doi.org/10.1109/TMC.2023.3321980

4. N. Fernandes, M. Dras, and A. McIver, "Generalised differential privacy for text document processing," in *Data Privacy Management, Cryptocurrencies and Blockchain Technology*, Springer, 2019, pp. 123–140. [Online]. Available: https://doi.org/10.1007/978-3-030-17138-4_6
5. L. Liu, X. Jiang, F. Zheng, H. Chen, G. J. Qi, H. Huang, and S. Ding, "A Bayesian federated learning framework with online Laplace approximation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 46, no. 1, pp. 1–16, 2024. [Online]. Available: https://doi.org/10.1109/TPAMI.2023.3330515
6. D. Truhn, S. Tayebi Arasteh, O. L. Saldanha, *et al.*, "Encrypted federated learning for secure decentralized collaboration in cancer image analysis," *Medical Image Analysis*, vol. 92, p. 103059, 2024. [Online]. Available: https://doi.org/10.1016/j.media.2023.103059
7. S. Dhiman, S. Nayak, G. K. Mahato, A. Ram, and S. K. Chakraborty, "Homomorphic encryption based federated learning for financial data security," in *2023 4th International Conference on Computing and Communication Systems (I3CS)*, 2023, pp. 1–6. [Online]. Available: https://doi.org/10.1109/I3CS58314.2023.10127423
8. Y. Lu, X. Huang, Y. Dai, S. Maharjan, and Y. Zhang, "Blockchain and federated learning for privacy-preserved data sharing in industrial IoT," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 6, pp. 4177–4186, 2019. [Online]. Available: https://doi.org/10.1109/TII.2019.2942190
9. Z. Wang, M. Wen, Y. Xu, Y. Zhou, J. H. Wang, and L. Zhang, "Communication compression techniques in distributed deep learning: A survey," *Journal of Systems Architecture*, vol. 142, p. 102927, 2023. [Online]. Available: https://doi.org/10.1016/j.sysarc.2023.102927
10. J. Kim, *et al.*, "Collective communication performance evaluation for distributed deep learning training," *Applied Sciences*, vol. 14, no. 12, p. 5100, 2024. [Online]. Available: https://doi.org/10.3390/app14125100
11. Y. Dong, Y. Wang, M. Gama, M. A. Mustafa, G. Deconinck, and X. Huang, "Privacy-preserving distributed learning for residential short-term load forecasting," *IEEE Internet of Things Journal*, 2024. [Online]. Available: https://doi.org/10.1109/JIOT.2024.3361973
12. T. Qi, F. Wu, C. Wu, L. He, Y. Huang, and X. Xie, "Differentially private knowledge transfer for federated learning," *Nature Communications*, vol. 14, no. 1, p. 3785, 2023. [Online]. Available: https://doi.org/10.1038/s41467-023-39632-9
13. F. Liang, Z. Zhang, H. Lu, V. C. Leung, Y. Guo, and X. Hu, "Communication-efficient large-scale distributed deep learning: A comprehensive survey," *arXiv preprint arXiv:2404.06114*, 2024. [Online]. Available: https://arxiv.org/abs/2404.06114
14. B. Ganguly, S. Hosseinalipour, K. T. Kim, C. G. Brinton, V. Aggarwal, D. J. Love, and M. Chiang, "Multi-edge server-assisted dynamic federated learning with an optimized floating aggregation point," *IEEE/ACM Transactions on Networking*, vol. 31, no. 6, pp. 2682–2697, 2023. [Online]. Available: https://doi.org/10.1109/TNET.2023.3268186
15. S. Ahn and E. Lim, "SoftMemoryBox II: A scalable, shared memory buffer framework for accelerating distributed training of large-scale deep neural networks," *IEEE Access*, vol. 8, pp. 207097–207111, 2020. [Online]. Available: https://doi.org/10.1109/ACCESS.2020.3038237