A. Computational Overhead Analysis

While our method achieves strong performance, we acknowledge that the spectral analysis in SNAA and graph repair in RLSR introduce modest computational overhead. Nevertheless, the overhead can be greatly reduced under GPU batch processing, sparse matrix multiplication and multiple clients partition, which makes our method practical on large graphs. For a k-layer GNN with batch size b and feature dimension f, T denotes moments order, while linear parameters include N, M, c (nodes, edges, classes), s (features aggregation steps), g (generated neighbors), K (selected clients per round), d (selected augmented nodes). We note that in our complexity analysis, N and M refer to the entire graph for server-side operations, but are scaled to the local subgraph size for client-side computations. For scenarios with extremely large local subgraphs, one could adopt approximate k' nearest-neighbor search to reduce client memory and time complexity to $\mathbf{O}(\mathbf{Nk'})$ and $\mathbf{O}(\mathbf{Nk'f})$, where $k' << N$. Thus, the computation of the local similarity matrix is highly efficient in practice. Analysis in Tab. 4 shows that FedSDR achieves top performance with reasonable overhead.

In addition, we analyze the computational complexity of the key operation $S_{\text{ide}} = \frac{\mathbf{D}^T\mathbf{L}\mathbf{D}}{\mathbf{D}^T\mathbf{D}}$ by leveraging the Compressed Sparse Row (CSR) format for sparse matrix multiplication. In the CSR format, the dominant computational cost of multiplying two sparse matrices $\mathbf{E}$ and $\mathbf{F}$ arises from the total number of inner-loop iterations, denoted as I. Let $n_\mathbf{E}$ and $n_\mathbf{F}$ denote the total number of non-zero entries in $\mathbf{E}$ and $\mathbf{F}$, respectively. This quantity I can be expressed as:

$$I = \sum_{i=0}^{N-1} r_\mathbf{F}(i) \cdot c_\mathbf{E}(i),$$

where $r_\mathbf{F}(i)$ denotes the number of non-zero entries in row i of $\mathbf{F}$, and $c_\mathbf{E}(i)$ denotes the number of non-zero entries in column i of $\mathbf{E}$. Noting that $\sum_{i=0}^{N-1} c_\mathbf{E}(i) = n_\mathbf{E}$, and assuming a relatively uniform distribution of non-zero entries across the rows of $\mathbf{F}$ such that $r_\mathbf{F}(i) \approx n_\mathbf{F}/N$, we obtain the approximation:

$$I \approx n_\mathbf{E} \cdot \frac{n_\mathbf{F}}{N},$$

which yields a computational complexity of $O(n_\mathbf{E} \cdot n_\mathbf{F}/N)$.

Complexity of $\mathbf{D}^T\mathbf{L}\mathbf{D}$. We analyze the computation in two sparse matrix multiplications. The degree matrix $\mathbf{D}$ is diagonal, so $n_\mathbf{D} = n_{\mathbf{D}^T} = N$. For the adjacency matrix $\mathbf{A}$ of an undirected graph without self-loops, the handshaking lemma gives $n_\mathbf{A} = 2M$, and therefore the Laplacian $\mathbf{L} = \mathbf{D} - \mathbf{A}$ contains $n_\mathbf{L} = n_\mathbf{A} + n_\mathbf{D} = 2M + N$ non-zero entries. Since directed graphs or the presence of self-loops would reduce the values of $n_\mathbf{A}$ and $n_\mathbf{L}$, the undirected graph without self-loops represents the worst-case computation.

- **Step 1: Compute $\mathbf{G} = \mathbf{D}^T\mathbf{L}$** This is a left multiplication by a diagonal matrix. The complexity is:

$$O\left(n_{\mathbf{D}^T} \cdot \frac{n_\mathbf{L}}{N}\right) = O\left(N \cdot \frac{2M+N}{N}\right) = O(2M+N).$$

  The resulting matrix $\mathbf{G}$ inherits the sparsity pattern of $\mathbf{L}$, so $n_\mathbf{G} = 2M + N$.
- **Step 2: Multiply $\mathbf{G}$ with $\mathbf{D}$.** This is a right multiplication by a diagonal matrix. The complexity is:

$$O\left(n_\mathbf{G} \cdot \frac{n_\mathbf{D}}{N}\right) = O\left((2M+N) \cdot \frac{N}{N}\right) = O(2M+N).$$

Thus, the total complexity for computing $\mathbf{D}^T\mathbf{L}\mathbf{D}$ is $O(2M+N) + O(2M+N) = O(M+N)$.

Complexity of $\mathbf{D}^T\mathbf{D}$. Since both matrices are diagonal, their multiplication takes:

$$O\left(n_{\mathbf{D}^T} \cdot \frac{n_\mathbf{D}}{N}\right) = O\left(N \cdot \frac{N}{N}\right) = O(N).$$

Complexity of Summation and Division. Summing all non-zero entries of $\mathbf{D}^T\mathbf{L}\mathbf{D}$ requires $O(M+N)$ time, and summing the N diagonal entries of $\mathbf{D}^T\mathbf{D}$ requires $O(N)$. The final scalar division costs $O(1)$. Therefore, the total complexity is $O(M+N) + O(N) + O(1) = O(M+N)$.

Overall Complexity. Combining all components yields:

$$O(M+N) + O(N) + O(M+N) = O(M+N).$$

This linear time complexity of S_{ide} with respect to the graph size confirms the practical efficiency of our method for large-scale graphs.

B. Datasets

Statistics and configurations of the datasets used in our experiments are provided in Tab. 5.

PubMed: PubMed [43] is a widely adopted citation network dataset in which nodes represent academic papers and edges correspond to citation relationships between them. Each node is associated with a word vector feature encoding the presence or absence of specific keywords in the corresponding paper. As a standard benchmark in graph-based machine learning, this dataset is commonly employed for node classification tasks, particularly in FL scenarios where data privacy must be preserved.

Coauthor-CS, Coauthor-Physics: Derived from the Microsoft Academic Graph, the Coauthor-CS and Coauthor-Physics datasets [44] originate from the KDD Cup 2016 challenge. These benchmark datasets represent academic collaboration networks, with nodes corresponding to authors and edges indicating co-authorship. Coauthor-CS comprises 18,333 nodes and 81,894 edges, featuring node attributes based on paper keywords and 15 distinct research fields as class labels. The larger Coauthor-Physics dataset contains 34,493 nodes and 247,962 edges, with similar node features and labels representing classification into 5 main research areas. Both datasets serve as established benchmarks for evaluating graph neural networks, particularly for node classification tasks, due to their realistic academic network structures and comprehensive feature representations.

Actor: The Actor dataset [40] is an actor co-occurrence network from Wikipedia, where nodes represent actors and edges indicate co-appearance in Wikipedia pages. Each node is characterized by a bag-of-words feature vector derived from the corresponding Wikipedia page content. The dataset includes five actor categories, determined through semantic analysis of their associated Wikipedia entries. As a standard benchmark in graph machine learning, it is widely used to evaluate node classification tasks and related graph-based learning problems.

Roman-empire: The Roman-empire dataset [5] is derived from the English Wikipedia article about the Roman Empire. Nodes represent word occurrences (including non-unique words), with the graph size reflecting the article length. Edges are based on two linguistic relationships: (1) sequential co-occurrence when words appear consecutively in the text, and (2) syntactic dependencies from the sentence parse trees. This construction yields a chain-like graph augmented with linguistic connections, capturing sequential and syntactic relationships between words.

ogbn-mag: The ogbn-mag dataset from the Open Graph Benchmark (OGB) facilitates node property prediction within a heterogeneous academic network derived from the Microsoft Academic Graph (MAG). This graph comprises four entity types—papers (736,389 nodes), authors (1.13 million nodes), institutions (8,740 nodes), and fields of study (59,965 nodes)—interconnected by directed relations such as authorship, citation, and affiliation. Each paper node possesses a 128-dimensional word2vec feature vector, while other lack initial features. The objective is a 349-class classification to predict the publishing venue of each paper. A temporally realistic split is employed, where papers published before 2018 are used for training, those from 2018 for validation, and papers since 2019 for testing, forecasting future trends based on historical data [19].

ogbn-products: The ogbn-products dataset from the Open Graph Benchmark (OGB) is designed for node property prediction within an Amazon product co-purchasing network. This large-scale, undirected, and unweighted graph contains approximately 2.4 million product nodes and 61.9 million edges representing co-purchase relationships. Each node is associated with a 100-dimensional feature vector generated from product descriptions using bag-of-words and PCA. The objective is a multi-class classification task to predict one of 47 top-level product categories. Reflecting a realistic scenario, the dataset is split by sales rank: the top 8% of popular products are used for training, the subsequent 2% for validation, and the remaining 90% for testing, thereby requiring predictions for less popular items [19].

C. Privacy Analysis

To analyze the privacy-utility trade-off, we evaluate FedSDR on PubMed under varying noise multipliers σ, keeping the gradient clipping threshold B and the failure probability δ fixed at 1.0 and 10^{-5}, respectively. As shown in Tab. 3, FedSDR maintains robust performance even under strict privacy guarantees. Interestingly, we observe a **slight performance improvement**, which suggests that the gradient clipping, combined with our structure repair, effectively prevents overfitting to structural noise.

Metric	No DP	Weak DP ($\sigma = 0.5$)	Strong DP ($\sigma = 1.0$)
Acc	82.57	**83.69** ↑1.12	**83.46** ↑0.89

Table 3. Accuracy under differential privacy (DP) constraints.

D. Additional Experiments

We comprehensively compare FedSDR with state-of-the-art methods under varying **corruption ratios** (the proportion of structurally corrupted clients) and **noise extents** (the proportion of edges randomly added and then deleted from the original graph in corrupted clients). Our experimental setup evaluates three corruption ratios of 0.3, 0.5, and 1 (the extreme case detailed in Tab. 1), with the noise extent and the pruning proportion α fixed at 0.5 and 0.3. In addition, we validate the robustness of FedSDR across three noise extents (0.3, 0.5, and 1), while keeping the corruption ratio at 0.5 and the pruning proportion α at 0.3 constant. Notably, as the corruption severity increases, competing methods exhibit significant performance degradation, whereas FedSDR maintains stable performance, demonstrating a substantial advantage. The best and second results are highlighted with bold and underline, respectively.

Methods	Client Mem	Server Mem	Client Time	Server Time
FedGTA	$\mathbf{O((b+s)f+f^2+sTc)}$	$O(Kf^2+KsTc)$	$O(sM(f+sNc)+N(f^2+c))$	$O(Kf+KsTc)$
FedTAD	$O((b+s)f+f^2+Nf+kMf)$	$O(Kf^2+dgf+kf^2)$	$\mathbf{O(sNMf+Nf^2)}$	$O(Kf+(k+N)f^2+kdgf)$
FedSDR	$O(N^2+f^2+kMf)$	$\mathbf{O(K+Kf^2)}$	$O(M+N+kMf+Nf^2+N^2f)$	$\mathbf{O(Kf+K)}$

Table 4. Complexity analysis among structure-related methods. Best in bold.

Dataset	Nodes	Edges	Classes	Features	Learning Rate	Rounds	Clients
PubMed	19,717	44,338	3	500	0.01	1,000	10
Coauthor-CS	18,333	81,894	15	6,805	0.005	1,000	50
Coauthor-Phy	34,493	247,962	5	8,415	0.01	1,000	100
Actor	7,600	29,926	5	931	0.002	1,000	20
Roman-empire	22,662	32,927	18	300	0.02	5,000	50
ogbn-mag	1,939,743	21,111,007	349	128	0.01	1,000	100
ogbn-products	2,449,029	61,859,140	47	100	0.01	1,000	100

Table 5. Statistics and configurations of datasets used in experiments.

Methods	PubMed	Coauthor-CS	Coauthor-Phy	Actor	Roman-empire	ogbn-mag	ogbn-products
FedAvg [ASTAT17]	81.83 ± 0.69	81.69 ± 0.47	89.08 ± 0.27	31.37 ± 0.58	39.23 ± 0.50	40.79 ± 0.57	73.34 ± 0.49
FedProx [arxiv18]	82.23 ± 0.68	82.05 ± 0.22	89.50 ± 0.29	$\underline{31.57 \pm 0.65}$	39.74 ± 0.54	$\underline{42.47 \pm 0.46}$	73.06 ± 0.47
Scaffold [ICML20]	40.45 ± 1.81	48.57 ± 2.43	79.88 ± 0.44	23.69 ± 0.46	17.90 ± 0.32	14.52 ± 0.42	66.28 ± 0.41
MOON [CVPR21]	76.65 ± 2.76	$\underline{83.36 \pm 0.18}$	$\mathbf{91.06 \pm 0.16}$	31.36 ± 0.69	$\underline{39.97 \pm 0.17}$	40.33 ± 0.37	73.47 ± 0.36
Ditto [ICML21]	78.92 ± 0.89	81.28 ± 0.75	88.61 ± 0.49	30.71 ± 0.27	38.26 ± 0.33	41.08 ± 0.79	71.95 ± 0.82
FedSage+ [NIPS21]	81.73 ± 0.68	81.92 ± 0.23	89.11 ± 1.02	30.95 ± 0.52	39.61 ± 0.69	39.89 ± 0.41	72.85 ± 0.40
FedProto [AAAI22]	82.01 ± 0.40	74.14 ± 0.29	86.70 ± 0.23	23.45 ± 0.29	13.93 ± 0.48	35.21 ± 0.56	69.20 ± 0.39
RHFL [CVPR22]	82.03 ± 0.53	82.18 ± 0.66	89.08 ± 0.41	31.06 ± 0.26	39.88 ± 0.45	42.04 ± 0.62	$\underline{74.58 \pm 0.57}$
FGSSL [IJCAI23]	82.09 ± 0.41	80.97 ± 0.57	89.94 ± 0.33	30.97 ± 0.52	33.16 ± 0.32	41.26 ± 0.63	72.32 ± 0.24
FED-PUB [ICML23]	80.27 ± 0.54	80.84 ± 0.56	87.90 ± 0.34	28.96 ± 0.73	38.39 ± 0.47	37.47 ± 0.29	71.53 ± 0.27
FedTAD [IJCAI24]	$\underline{82.62 \pm 0.43}$	73.16 ± 1.55	OOM	30.79 ± 0.45	39.83 ± 0.80	OOM	OOM
AdaFGL [ICDE24]	81.32 ± 0.71	82.17 ± 0.37	88.75 ± 0.48	31.21 ± 0.59	39.28 ± 0.50	40.36 ± 0.78	72.94 ± 0.66
FedGTA [VLDB24]	82.20 ± 0.75	81.03 ± 0.60	85.77 ± 0.16	31.30 ± 0.50	38.80 ± 1.12	38.74 ± 0.69	73.78 ± 0.53
FedSSP [NIPS24]	79.90 ± 0.32	81.22 ± 0.39	88.04 ± 0.50	30.74 ± 0.81	37.52 ± 0.65	37.25 ± 0.47	72.02 ± 0.35
FedTGE [ICLR25]	78.89 ± 0.73	78.17 ± 0.80	87.25 ± 0.92	29.48 ± 0.79	36.26 ± 0.37	38.35 ± 0.86	70.23 ± 0.83
FedATH [ICML25]	78.04 ± 0.55	79.84 ± 0.49	87.63 ± 0.61	30.29 ± 0.46	36.43 ± 0.41	38.19 ± 0.39	71.88 ± 0.76
FedIIH [AAAI25]	79.32 ± 0.46	80.87 ± 0.42	88.16 ± 0.59	30.43 ± 0.67	38.65 ± 0.53	38.94 ± 0.40	73.36 ± 0.54
FedSDR (ours)	$\mathbf{84.07 \pm 0.48}$	$\mathbf{83.43 \pm 0.39}$	$\underline{90.72 \pm 0.43}$	$\mathbf{33.30 \pm 0.42}$	$\mathbf{41.58 \pm 0.38}$	$\mathbf{46.88 \pm 0.21}$	$\mathbf{80.57 \pm 0.42}$

Table 6. Corruption Ratio $= 0.3$, Noise Extent $= 0.5$, $\alpha = 0.3$

Methods	PubMed	Coauthor-CS	Coauthor-Phy	Actor	Roman-empire	ogbn-mag	ogbn-products
FedAvg [ASTAT17]	81.28 ± 2.02	81.26 ± 0.26	88.20 ± 0.22	31.29 ± 0.53	39.14 ± 0.60	41.58 ± 0.81	$\underline{72.85 \pm 0.24}$
FedProx [arxiv18]	80.82 ± 0.96	$\underline{82.48 \pm 0.51}$	88.68 ± 0.13	$\underline{31.56 \pm 0.59}$	39.26 ± 0.50	42.06 ± 0.27	72.83 ± 0.87
Scaffold [ICML20]	40.71 ± 0.90	44.72 ± 4.54	80.21 ± 1.61	23.06 ± 1.37	16.76 ± 1.86	14.07 ± 2.02	62.51 ± 2.03
MOON [CVPR21]	77.09 ± 2.59	80.92 ± 0.54	$\underline{90.08 \pm 0.17}$	31.04 ± 0.64	40.41 ± 0.22	42.34 ± 0.52	72.07 ± 0.22
Ditto [ICML21]	77.95 ± 0.85	80.31 ± 0.82	86.91 ± 0.32	30.03 ± 0.28	38.32 ± 0.24	$\underline{42.85 \pm 1.01}$	71.73 ± 0.25
FedSage+ [NIPS21]	79.91 ± 0.82	81.38 ± 0.57	87.30 ± 0.81	31.42 ± 0.43	39.03 ± 0.57	41.11 ± 0.47	72.36 ± 0.38
FedProto [AAAI22]	79.95 ± 0.58	72.46 ± 0.43	85.55 ± 0.21	23.50 ± 0.28	15.94 ± 0.13	36.04 ± 0.59	68.13 ± 0.44
RHFL [CVPR22]	79.86 ± 0.67	82.07 ± 0.49	87.34 ± 0.35	31.40 ± 0.48	38.33 ± 0.45	42.31 ± 0.92	72.76 ± 0.29
FGSSL [IJCAI23]	78.36 ± 0.46	81.48 ± 0.42	88.60 ± 0.76	31.31 ± 0.30	34.58 ± 0.56	40.38 ± 0.30	71.64 ± 0.34
FED-PUB [ICML23]	76.82 ± 0.59	79.79 ± 0.37	86.28 ± 0.31	30.06 ± 0.35	37.12 ± 0.65	39.51 ± 0.56	71.22 ± 0.46
FedTAD [IJCAI24]	80.93 ± 0.58	74.81 ± 1.38	OOM	31.25 ± 0.57	$\underline{40.53 \pm 0.46}$	OOM	OOM
AdaFGL [ICDE24]	78.74 ± 0.60	80.06 ± 0.74	87.90 ± 0.65	31.06 ± 0.32	40.36 ± 0.63	41.67 ± 0.30	71.24 ± 0.65
FedGTA [VLDB24]	$\underline{81.30 \pm 0.77}$	81.22 ± 0.49	88.28 ± 0.18	31.25 ± 0.22	39.64 ± 0.76	41.12 ± 0.35	72.01 ± 0.63
FedSSP [NIPS24]	78.24 ± 0.81	80.12 ± 0.71	86.56 ± 0.92	30.58 ± 0.73	38.15 ± 0.62	40.21 ± 0.58	71.81 ± 0.32
FedTGE [ICLR25]	78.22 ± 1.18	77.62 ± 0.84	86.13 ± 0.91	31.05 ± 0.88	37.04 ± 0.79	38.31 ± 0.37	69.57 ± 0.90
FedATH [ICML25]	77.42 ± 0.63	79.08 ± 0.73	86.65 ± 0.50	30.11 ± 0.53	37.70 ± 0.50	39.87 ± 0.46	69.85 ± 0.48
FedIIH [AAAI25]	78.67 ± 0.96	80.15 ± 0.75	87.34 ± 0.65	29.94 ± 0.76	38.86 ± 0.52	41.35 ± 0.68	72.83 ± 0.51
FedSDR (ours)	$\mathbf{84.06 \pm 0.44}$	$\mathbf{83.10 \pm 0.32}$	$\mathbf{90.50 \pm 0.23}$	$\mathbf{33.10 \pm 0.50}$	$\mathbf{45.12 \pm 0.36}$	$\mathbf{48.06 \pm 0.20}$	$\mathbf{80.23 \pm 1.20}$

Table 7. Corruption Ratio $= 0.5$, Noise Extent $= 0.5$, $\alpha = 0.3$

Methods	PubMed	Coauthor-CS	Coauthor-Phy	Actor	Roman-empire	ogbn-mag	ogbn-products
FedAvg [ASTAT17]	82.60 ± 0.22	81.47 ± 0.27	88.97 ± 0.22	31.07 ± 0.47	38.82 ± 0.42	41.07 ± 0.61	72.68 ± 0.35
FedProx [arxiv18]	82.44 ± 0.65	81.87 ± 0.26	89.60 ± 0.52	31.47 ± 0.43	39.49 ± 0.84	41.09 ± 0.38	72.50 ± 0.40
Scaffold [ICML20]	41.90 ± 0.41	50.70 ± 1.58	79.61 ± 2.18	22.07 ± 0.98	17.57 ± 0.33	13.77 ± 1.22	64.76 ± 1.05
MOON [CVPR21]	76.68 ± 3.39	$\underline{82.09 \pm 0.45}$	$\underline{90.40 \pm 0.37}$	$\underline{31.85 \pm 1.31}$	40.17 ± 0.26	$\underline{42.56 \pm 0.42}$	72.01 ± 0.31
Ditto [ICML21]	78.32 ± 0.82	81.24 ± 0.45	87.39 ± 0.43	30.50 ± 0.30	38.46 ± 0.68	42.34 ± 0.80	71.92 ± 0.55
FedSage+ [NIPS21]	80.50 ± 0.70	81.60 ± 0.52	88.56 ± 0.83	31.00 ± 0.40	40.10 ± 0.65	40.57 ± 0.40	72.23 ± 0.46
FedProto [AAAI22]	81.30 ± 0.43	74.27 ± 0.31	86.42 ± 0.14	23.04 ± 1.07	14.52 ± 0.19	35.66 ± 0.58	68.60 ± 0.41
RHFL [CVPR22]	80.06 ± 0.60	81.51 ± 0.74	88.23 ± 0.92	31.22 ± 0.45	38.75 ± 0.53	42.35 ± 0.78	$\underline{73.24 \pm 0.59}$
FGSSL [IJCAI23]	81.39 ± 0.51	80.51 ± 0.30	89.95 ± 0.24	30.88 ± 0.68	33.95 ± 0.80	41.15 ± 0.36	72.25 ± 0.32
FED-PUB [ICML23]	78.12 ± 0.68	80.34 ± 0.42	86.89 ± 0.43	29.28 ± 0.33	38.50 ± 0.65	39.22 ± 0.55	71.47 ± 0.50
FedTAD [IJCAI24]	$\underline{82.67 \pm 0.31}$	73.25 ± 1.66	OOM	30.93 ± 0.98	$\underline{40.30 \pm 0.37}$	OOM	OOM
AdaFGL [ICDE24]	79.86 ± 0.72	81.50 ± 0.61	88.45 ± 0.58	31.15 ± 0.42	39.34 ± 0.67	40.21 ± 0.43	72.63 ± 0.64
FedGTA [VLDB24]	82.19 ± 0.45	81.26 ± 0.27	88.87 ± 0.07	31.55 ± 0.30	40.22 ± 0.40	40.80 ± 0.60	72.93 ± 0.40
FedSSP [NIPS24]	79.17 ± 0.70	80.50 ± 0.60	87.79 ± 0.70	30.70 ± 0.70	37.26 ± 0.60	38.58 ± 0.50	71.83 ± 0.51
FedTGE [ICLR25]	78.48 ± 0.67	77.95 ± 0.52	86.39 ± 0.74	30.16 ± 0.41	36.38 ± 0.63	37.29 ± 0.58	69.90 ± 0.49
FedATH [ICML25]	77.73 ± 0.48	79.21 ± 0.61	87.14 ± 0.53	30.43 ± 0.37	36.68 ± 0.44	38.02 ± 0.39	70.87 ± 0.62
FedIIH [AAAI25]	78.81 ± 0.55	80.60 ± 0.47	87.75 ± 0.68	31.19 ± 0.52	37.95 ± 0.51	39.26 ± 0.43	72.40 ± 0.57
FedSDR (ours)	$\mathbf{84.57 \pm 0.49}$	$\mathbf{82.82 \pm 0.32}$	$\mathbf{90.45 \pm 0.14}$	$\mathbf{33.37 \pm 0.50}$	$\mathbf{44.36 \pm 0.21}$	$\mathbf{47.50 \pm 0.30}$	$\mathbf{80.80 \pm 0.40}$

Table 8. Corruption Ratio $= 0.5$, Noise Extent $= 0.3$, $\alpha = 0.3$

Methods	PubMed	Coauthor-CS	Coauthor-Phy	Actor	Roman-empire	ogbn-mag	ogbn-products
FedAvg [ASTAT17]	78.89 ± 0.21	76.27 ± 0.76	86.83 ± 0.50	30.97 ± 0.50	39.15 ± 0.71	42.26 ± 0.65	$\underline{72.43 \pm 0.82}$
FedProx [arxiv18]	78.59 ± 1.38	76.35 ± 0.07	87.05 ± 0.68	31.54 ± 0.53	38.77 ± 0.37	41.28 ± 0.37	72.14 ± 0.64
Scaffold [ICML20]	42.60 ± 1.50	42.46 ± 0.90	77.69 ± 1.16	24.02 ± 0.34	17.91 ± 0.36	17.29 ± 2.15	59.43 ± 1.97
MOON [CVPR21]	71.84 ± 1.66	$\underline{76.91 \pm 0.68}$	$\underline{88.59 \pm 0.55}$	31.55 ± 0.83	39.66 ± 0.22	41.83 ± 0.72	69.86 ± 0.51
Ditto [ICML21]	77.37 ± 0.91	75.76 ± 0.67	86.97 ± 0.43	30.95 ± 0.31	39.71 ± 0.52	41.15 ± 0.87	71.44 ± 0.73
FedSage+ [NIPS21]	78.35 ± 0.78	75.04 ± 0.56	87.28 ± 0.64	30.68 ± 0.49	40.58 ± 0.61	41.52 ± 0.46	70.55 ± 0.39
FedProto [AAAI22]	78.88 ± 1.06	69.41 ± 0.24	83.72 ± 0.20	23.38 ± 0.67	17.55 ± 0.25	36.45 ± 0.63	68.42 ± 0.87
RHFL [CVPR22]	78.43 ± 0.72	75.87 ± 0.81	86.69 ± 0.57	31.33 ± 0.54	$\underline{41.36 \pm 0.48}$	$\underline{42.54 \pm 0.63}$	72.11 ± 0.45
FGSSL [IJCAI23]	$\underline{79.04 \pm 1.95}$	74.50 ± 0.75	88.10 ± 0.61	31.63 ± 1.03	33.29 ± 0.20	42.27 ± 0.54	70.81 ± 0.76
FED-PUB [ICML23]	75.71 ± 0.62	76.56 ± 0.41	85.41 ± 0.58	30.72 ± 0.37	39.15 ± 0.59	39.76 ± 0.52	70.66 ± 0.83
FedTAD [IJCAI24]	78.68 ± 0.87	70.56 ± 1.41	OOM	31.23 ± 0.47	39.56 ± 0.41	OOM	OOM
AdaFGL [ICDE24]	77.63 ± 0.88	76.77 ± 0.65	87.53 ± 0.49	31.48 ± 0.42	41.06 ± 0.57	42.22 ± 0.34	70.43 ± 0.71
FedGTA [VLDB24]	78.67 ± 3.10	73.59 ± 0.37	86.60 ± 0.50	$\underline{31.90 \pm 0.55}$	38.72 ± 0.35	41.85 ± 0.41	71.76 ± 0.68
FedSSP [NIPS24]	77.83 ± 0.54	75.26 ± 0.47	86.21 ± 0.68	31.24 ± 0.61	40.42 ± 0.53	40.71 ± 0.44	69.17 ± 0.79
FedTGE [ICLR25]	76.50 ± 0.73	73.63 ± 0.59	85.75 ± 0.81	30.49 ± 0.46	38.44 ± 0.67	39.80 ± 0.54	68.84 ± 0.71
FedATH [ICML25]	77.17 ± 0.42	76.42 ± 0.57	86.52 ± 0.49	30.28 ± 0.38	38.77 ± 0.41	40.43 ± 0.47	69.50 ± 0.53
FedIIH [AAAI25]	78.51 ± 0.64	76.25 ± 0.50	87.19 ± 0.72	31.04 ± 0.43	37.86 ± 0.56	41.71 ± 0.52	71.95 ± 0.60
FedSDR (ours)	$\mathbf{83.75 \pm 0.25}$	$\mathbf{80.64 \pm 0.39}$	$\mathbf{89.52 \pm 0.24}$	$\mathbf{33.50 \pm 0.89}$	$\mathbf{46.40 \pm 0.61}$	$\mathbf{46.73 \pm 0.33}$	$\mathbf{79.36 \pm 0.47}$

Table 9. Corruption Ratio $= 0.5$, Noise Extent $= 1$, $\alpha = 0.3$