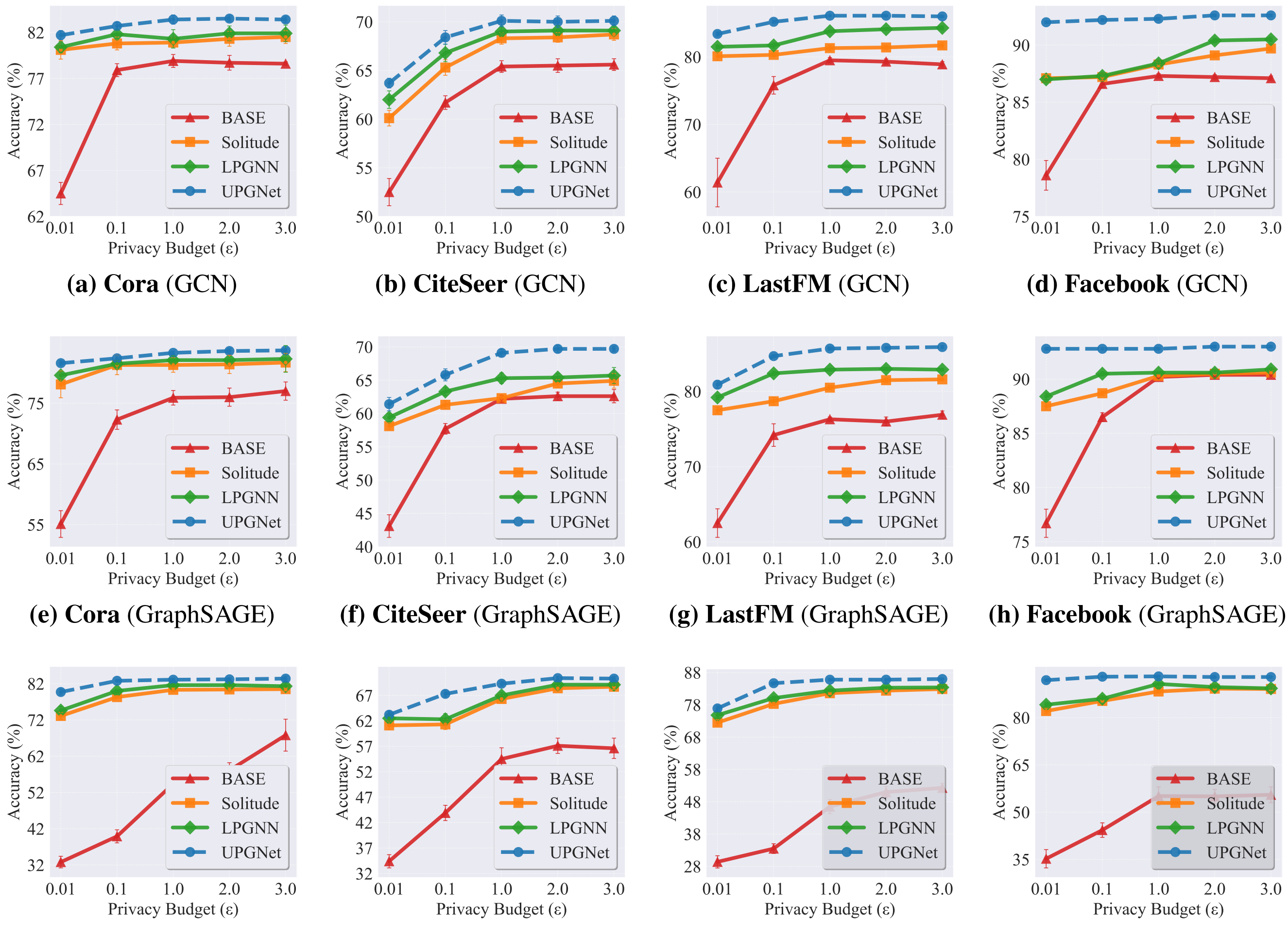


(a) Cora (GCN) **(b) CiteSeer** (GCN) **(c) LastFM** (GCN) **(d) Facebook** (GCN)

(e) Cora (GraphSAGE) **(f) CiteSeer** (GraphSAGE) **(g) LastFM** (GraphSAGE) **(h) Facebook** (GraphSAGE)

(i) Cora (GAT) **(j) CiteSeer** (GAT) **(k) LastFM** (GAT) **(l) Facebook** (GAT

Figure 1: Performance of UPGNET and other baselines. X-axis represents ϵ and y-axis represents test accuracy (%).

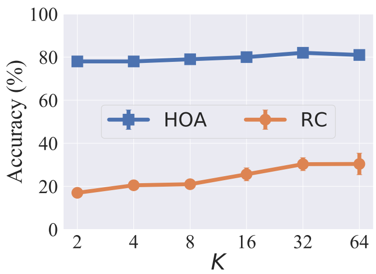


Figure 2: Comparison of HOA and Residual Connection (RC) (Dataset: Cora, $\epsilon = 0.01$). HOA demonstrates significantly better classification accuracy in private graph learning compared to Residual Connection.

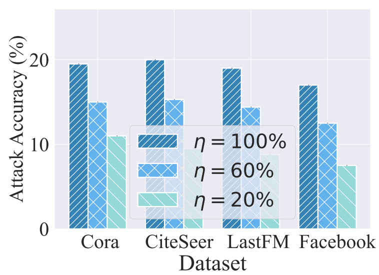


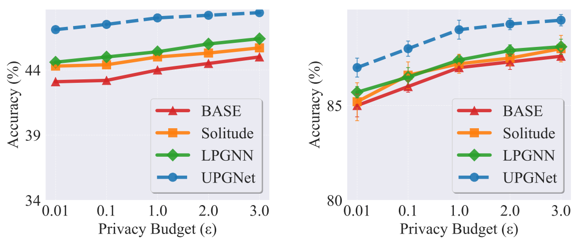
Figure 3: Attack accuracy with varying proportions (η) of neighboring information accessible to the attacker. When η is small (a more realistic scenario), UPGNET demonstrates stronger defense performance.

Table 1: Hyperparameters and optimization settings for LPGNN.

Hyperparameter	Value Range	Hyperparameter	Value Range
optimal parameter selection	grid search	optimizer	Adam optimizer
privacy budget	$\{0.01, 0.1, 1.0, 2.0, 3.0\}$	learning rate	$\{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 0\}$
KProp step	$\{0, 2, 4, 6, 8, 16\}$	weight decay	$\{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 0\}$
GNN	GCN, GraphSAGE, GAT	dropout rate	$\{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 0\}$

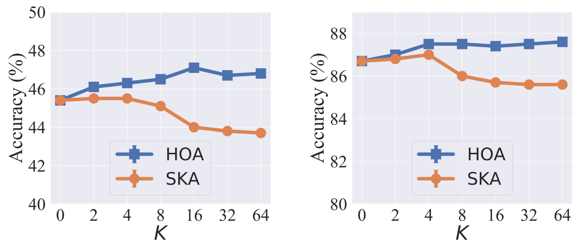
Table 2: Statistics of heterophilic graph datasets.

Dataset	#Classes	#Nodes	#Edges	#Features
Flickr	7	89,250	899,756	500
Reddit	41	232,965	114,615,892	602



(a) Flickr (b) Reddit

Figure 4: Performance comparison of UPGNet and other baselines on Flickr and Reddit. X-axis represents ϵ and y-axis represents test accuracy (%). UPGNet exhibits superior performance compared to other baselines.



(a) Flickr (b) Reddit

Figure 5: Effect of HOA vs. SKA on graph learning performance across various steps $K \in \{2, 4, 8, 16, 32, 64\}$. HOA demonstrates its superior denoising capability on heterophilic datasets (Flickr and Reddit).

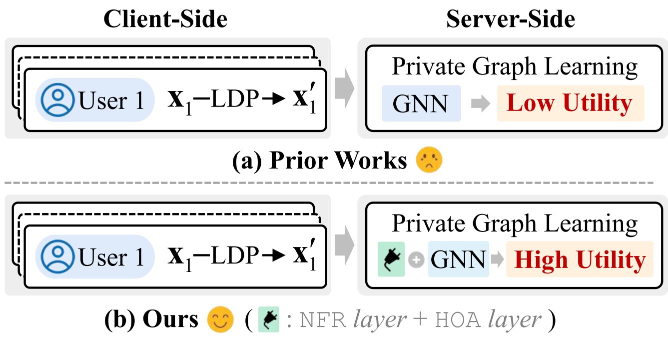
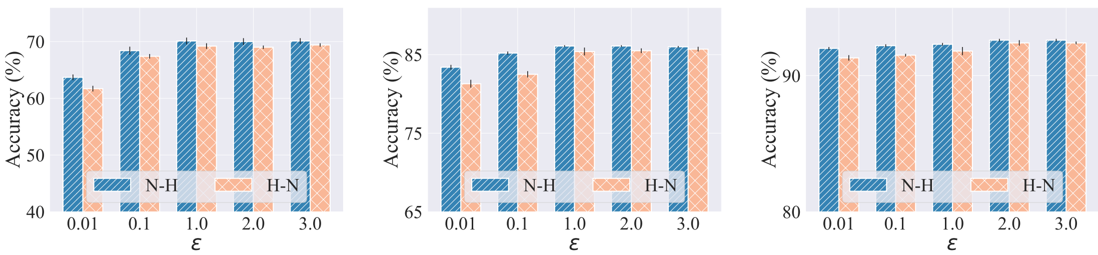


Figure 6: Comparison of **(a) prior works** and **(b) ours** in the locally private graph learning scenario. The scenario comprises a cloud server and multiple users situated across different clients. Users' sensitive node features $\mathbf{x}$ are perturbed to $\mathbf{x}'$ using LDP before uploading to the cloud server for graph learning. Our approach achieves higher utility by integrating than prior works.

Table 3: Comparison of our NFR (without HOA) with dropout and group Lasso ($\epsilon = 0.01$, GCN). The values in the table represent accuracy (%). NFR demonstrates significantly better learning utility compared to other sparsity-inducing techniques.

Baseline	Cora	CiteSeer	LastFM	Facebook
Dropout	63.4	52.7	61.3	77.6
Group Lasso	57.6	50.5	57.1	78.9
Ours	**71.3**	**57.2**	**67.1**	**84.9**



(a) CiteSeer (b) LastFM (c) Facebook

Figure 7: Performance of UPGNet in H-N vs. N-H architectures.