

MORE EXPERIMENT RESULTS ON EFFACE

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1. MORE EXPERIMENT RESULTS

Datasets, Models, and Federated Frameworks. We test on 5 datasets in image classification: MNIST, Fashion-MNIST, SVHN, CIFAR-10 and CIFAR-100 [1, 2, 3, 4]. We set 50 clients to smaller datasets (MNIST and Fashion-MNIST), and 50 clients to the others for scalability evaluation across client count and dataset complexity. We use CNN with 2 convolutional and 2 fully connected layers for MNIST and Fashion-MNIST, ResNet-18 for SVHN and CIFAR-10, and ResNet-34 for CIFAR-100 [5]. We adopt non-i.i.d. partition following the Dirichlet distribution with $\alpha = 0.5$.

Table 1. Unlearning performance on MNIST.

Methods	CA (\uparrow)	BA (\downarrow)	ET (\downarrow)	CC (\downarrow)
FedRetrain	99.03(0.10)	0.22(0.05)	2064.00	7893.45
FedGD	99.07(0.08)	99.81(0.02)	2064.41	7893.45
FedGA	86.54(1.01)	2.22(1.42)	154.83	1381.35
FedPSGA	96.45(0.75)	2.74(1.18)	173.16	1223.39
FedGB	98.30(0.26)	1.60(0.75)	543.71	4999.18
FedUOSC	98.29(0.26)	1.60(0.75)	552.17	2499.59
NoT	98.20(0.14)	0.60 (0.07)	2057.31	7893.45
FedRL	98.83 (0.04)	0.86(0.49)	675.36	5709.43
EFFACE	98.41(0.22)	1.16(0.85)	452.96	78.98

Table 2. Unlearning performance on Fashion-MNIST.

Methods	CA (\uparrow)	BA (\downarrow)	ET (\downarrow)	CC (\downarrow)
FedRetrain	91.72(0.12)	1.65(0.16)	2062.94	7893.45
FedGD	91.60(0.17)	96.50(0.05)	2052.01	7893.45
FedGA	77.50(0.70)	0.57(0.84)	110.25	1184.02
FedPSGA	86.73(0.61)	6.36(1.28)	125.82	1223.39
FedGB	89.89(0.13)	2.31(1.69)	208.50	1933.89
FedUOSC	89.94(0.30)	2.50(1.99)	209.39	966.95
NoT	88.61(0.52)	17.85(5.20)	2063.69	7893.45
FedRL	91.47 (0.20)	0.13 (0.02)	810.05	2682.79
EFFACE	90.39(0.14)	2.07(1.82)	807.74	79.02

Table 3. Unlearning performance on SVHN.

Methods	CA (\uparrow)	BA (\downarrow)	ET (\downarrow)	CC (\downarrow)
FedRetrain	96.25(0.08)	0.41(0.06)	6920.31	85250.56
FedGD	96.40(0.08)	99.00(0.15)	6837.16	34100.23
FedGA	94.52(0.68)	1.63(0.33)	324.36	12787.58
FedPSGA	95.78(0.31)	1.88(0.58)	345.72	10656.33
FedGB	96.26(0.10)	0.10(0.08)	271.89	9235.48
FedUOSC	96.08(0.41)	0.76(0.90)	270.88	4617.74
NoT	95.92(0.05)	2.31(3.14)	6853.64	34100.23
FedRL	95.22(0.35)	0.01 (0.01)	953.34	9362.75
EFFACE	96.36 (0.04)	0.13(0.02)	585.78	425.92

Table 4. Unlearning performance on CIFAR-10.

Methods	CA (\uparrow)	BA (\downarrow)	ET (\downarrow)	CC (\downarrow)
FedRetrain	92.44(0.24)	0.59(0.11)	4759.63	85250.56
FedGD	92.15(0.08)	96.23(0.19)	4827.12	85250.56
FedGA	90.24(0.05)	0.09(0.07)	138.14	12787.58
FedPSGA	90.96(0.27)	0.41(0.28)	144.32	10656.33
FedGB	91.54(0.15)	1.01(0.46)	131.06	9377.56
FedUOSC	91.72(0.17)	0.63(0.41)	133.68	4688.78
NoT	89.12(0.21)	21.87(21.37)	4834.32	85250.56
FedRL	91.54(1.39)	0.06 (0.02)	440.63	9625.28
EFFACE	91.75 (0.36)	0.36(0.03)	400.16	426.25

Table 5. Unlearning performance on CIFAR-100.

Methods	CA (\uparrow)	BA (\downarrow)	ET (\downarrow)	CC (\downarrow)
FedRetrain	73.20(0.45)	0.19(0.02)	7631.58	162721.95
FedGD	73.08(0.03)	92.08(0.47)	7562.71	162721.95
FedGA	72.57(0.10)	0.05(0.02)	177.98	24408.29
FedPSGA	72.94(0.07)	1.79(0.45)	184.66	20340.24
FedGB	73.02(0.05)	0.14(0.13)	180.02	19526.63
FedUOSC	72.99(0.09)	0.26(0.31)	180.09	9763.32
NoT	67.25(0.52)	29.24(24.42)	7648.41	162721.95
FedRL	72.50(0.42)	0.04 (0.01)	579.76	19660.93
EFFACE	73.05 (0.11)	0.12(0.06)	190.33	813.61

2. REFERENCES

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