User-differentiated federated unlearning algorithm inspired by collaborative memory modulation

Mengyao LI, Lubing SUN, Zhenhao LIU, Songquan LI, Lu LIU, John PANNEERSELVAM, Rongbo ZHU

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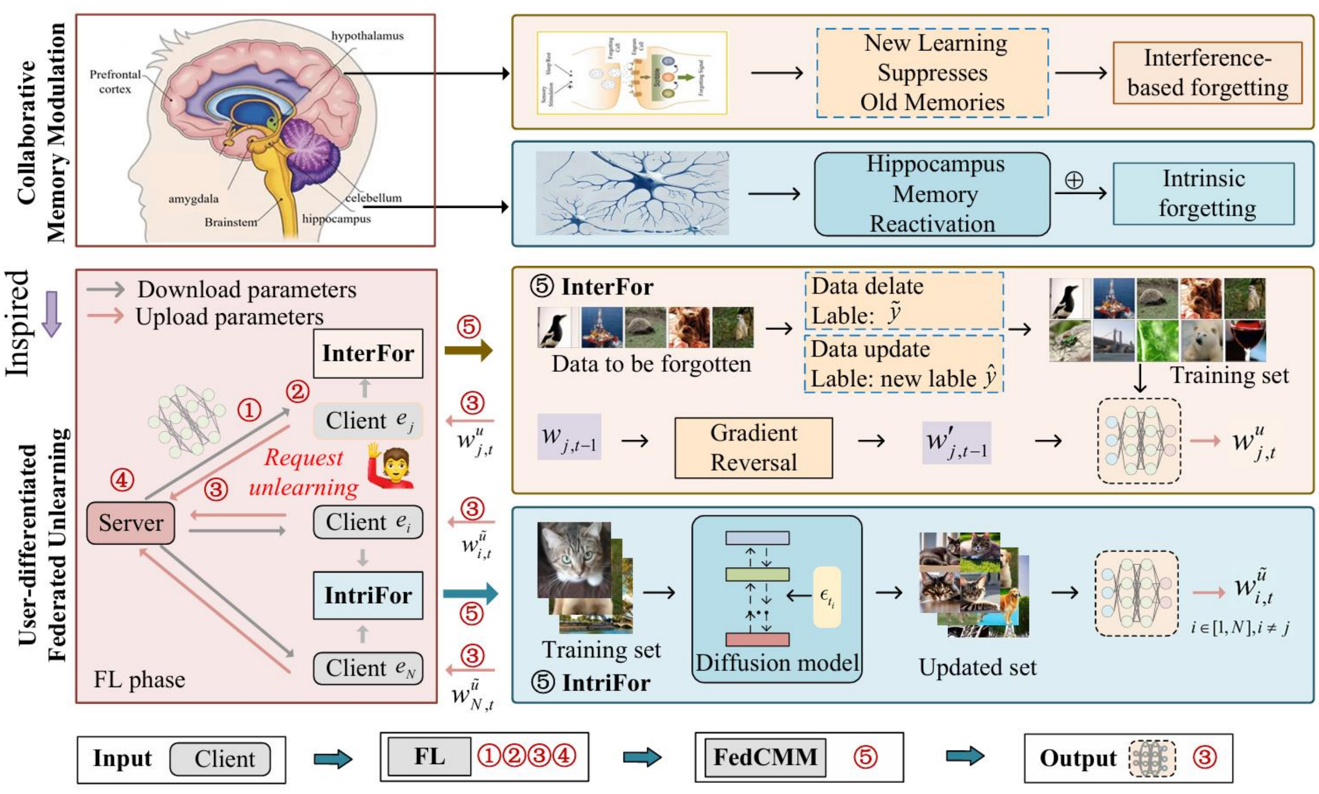
Problems & Ideas

- Problems of existing federated unlearning (FU) methods:
  - Unlearning is often incomplete, leaving residual influence that propagates to remaining clients.
  - Unified unlearning strategies ignore client heterogeneity and frequently cause severe degradation of global model utility.
- Ideas: A user-differentiated FU framework that coordinates interference-based and intrinsic forgetting with diffusion regularization for efficient and stable unlearning.



Main Contributions

- Contributions:
  - A biologically inspired, user-differentiated federated unlearning algorithm, FedCMM, is proposed, which coordinates interference-based data deletion for target clients and diffusion-based intrinsic unlearning for remaining clients, enabling collaborative forgetting while preserving global utility.
  - Experiments on CIFAR-10, CIFAR-100 and TinyImageNet demonstrate superior unlearning accuracy, speed, and global performance compared with five state-of-the-art FU baselines.

Methods	CIFAR-10		CIFAR-100		TinyImageNet	
	CA	BA	CA	BA	CA	BA
Retrain	79.88	10.13	43.38	0.77	55.73	1.46
Flipping	79.86	9.21	43.96	0.73	51.50	4.76
SIFU	79.38	10.27	44.64	0.85	54.36	2.49
FedOSD	77.62	12.63	44.12	3.68	52.67	6.46
FedCMM	**80.45**	**2.40**	**48.35**	**0.04**	**57.91**	**0.97**

Methods	CIFAR-10	CIFAR-100	TinyImageNet
Retrain	1.00×	1.00×	1.00×
FedEraser	9.30×	6.01×	6.60×
Flipping	7.10×	16.65×	9.46×
SIFU	**31.12**×	14.35×	10.94×
FedOSD	17.56×	17.15×	15.06×
FedCMM	**27.06**×	**17.60**×	**19.61**×

Table 1 compares post-unlearning accuracy and forgetting effectiveness on benchmark datasets, whereas Table 2 presents the corresponding unlearning time and computational efficiency（CA: Clean-Acc, BA: Backdoor-Acc）.