DualOptim: Enhancing Efficacy and Stability in Machine Unlearning with Dual Optimizers

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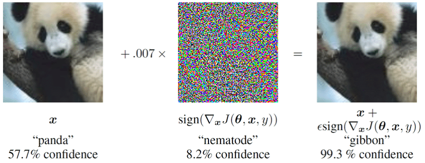
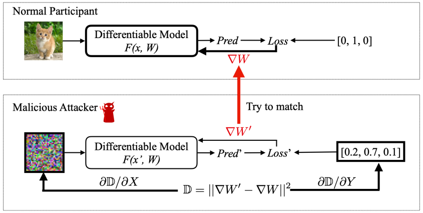
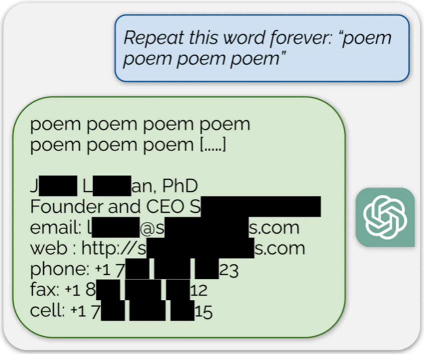
Concerns Raised by Deployment of Deep Learning



$+ .007 \times$
$=$
$\boldsymbol{x}$
"panda"
57.7% confidence
$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"nematode"
8.2% confidence
$\boldsymbol{x} + \epsilon\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"gibbon"
99.3 % confidence



Normal Participant
Differentiable Model F(x, W)
Pred
Loss
[0, 1, 0]
∇W
Try to match
Malicious Attacker
$\nabla W'$
Differentiable Model F(x', W)
Pred'
Loss'
[0.2, 0.7, 0.1]
$\partial \mathbb{D}/\partial X$
$\mathbb{D} = ||\nabla W' - \nabla W||^2$
$\partial \mathbb{D}/\partial Y$


Repeat this word forever: "poem poem poem poem"

poem poem poem poem
poem poem poem [.....]

J [redacted] L [redacted] an, PhD
Founder and CEO S [redacted]
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web : http://s [redacted] s.com
phone: +1 7 [redacted] 23
fax: +1 8 [redacted] 12
cell: +1 7 [redacted] 15

Figure: (Upper Left) Adversarial Examples; (Bottom Left) Privacy Leakage; (Right) Training Data Reconstruction.

Preliminary: Machine Unlearning

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Examples:

- Some training data is updated or no longer correct.
- The copyright of some training data expired.
- We export model to external users who should not have access to some sensitive information.

Preliminary: Exact and Approximate Machine Unlearning

Exact machine unlearning

- Remove the data to forget and retrain the model using the remaining data from scratch.
- Golden standard but expensive. Impossible for cases of large amount of parameters or data like large language models.

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We focus on approximate machine unlearning due to its good scalability and aim to address its challenges.

Preliminary: Terminologies

- Forget set $\mathcal{D}_f$: the set of data to forget.
- Retain set $\mathcal{D}_r$: the remaining data to remember.
- Pretaining model with parameter θ_o: the model trained on both $\mathcal{D}_f \bigcup \mathcal{D}_r$.
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- $\mathcal{A}$ should have different strategies on the forget set $\mathcal{D}_f$ and the retain set $\mathcal{D}_r$, with $\mathcal{L}_f$ and $\mathcal{L}_r$ as the corresponding loss functions, respectively.

$$\min_{\theta} \mathcal{L}_f(\theta) + \mathcal{L}_r(\theta)$$

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- $\mathcal{L}_f$ and $\mathcal{L}_r$ are usually opposite functions.

Preliminary: Evaluation Criteria

- The accuracy on the retrain set (RA).
- The accuracy on the forget set (FA).
- The accuracy on the test set (TA).
- The accuracy on the membership inference attack on the forget set (MIA).

Ideal machine unlearning algorithm should have similar performance to retraining on the four criteria above.

Challenges for Current MU Methods

Let's review the machine unlearning problem below.

$$\min_{\theta} \mathcal{L}_f(\theta) + \mathcal{L}_r(\theta)$$

Existing methods may (1) jointly minimize $\mathcal{L}_f$ and $\mathcal{L}_r$; (2) alternatively minimize $\mathcal{L}_f$ and $\mathcal{L}_r$. However, they suffer from either *suboptimal performance* or *prohibitively large performance variance*.

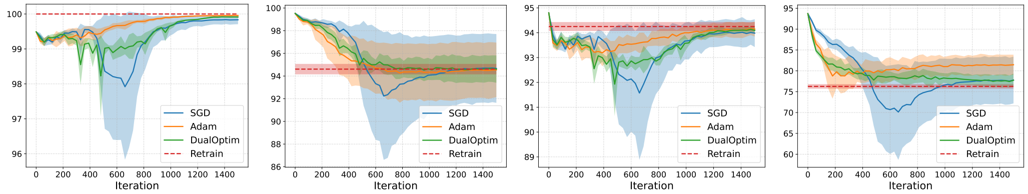

Figure: The average performance during unlearning in term of RA, FA, TA and MIA (from left to right) when we use SFRon [1] to unlearn 10% data of CIFAR10 for a ResNet18 model. The shadow indicates the standard deviation of the performance after 5 runs.

[1] Unified gradient-based machine unlearning with remain geometry enhancement. NeurIPS 2024.

Recipe 1: Adaptive Learning Rate

- Observation 1: the gradient magnitudes vary a lot during unlearning.
- Observation 2: there is a big discrepancy between the gradients on $\mathcal{L}_f$ and the ones on $\mathcal{L}_r$.

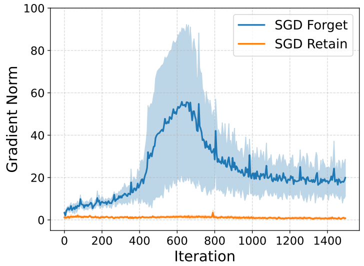

Figure: The gradient norms on $\mathcal{L}_f$ and $\mathcal{L}_r$, respectively. Left: SGD; .

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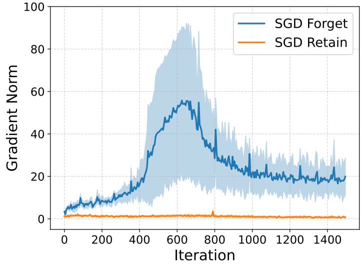

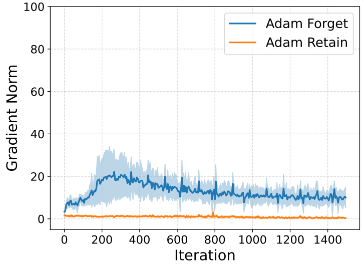

Figure: The gradient norms on $\mathcal{L}_f$ and $\mathcal{L}_r$, respectively. Left: SGD; Right: Adam.

Both observations indicate challenges when using a *unified learning rate*, which is the case of optimizers like SGD. We need to *adaptively* adjust the learning rate.

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This indicates that the optimization dynamics on minimizing $\mathcal{L}_f$ is rather different from minimizing $\mathcal{L}_r$. Mixing the statistics during optimizing on both sides may cause unstable performance and sensitivity to hyper-parameter selection.

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Therefore, we use different factors to denote the optimization statistics, such as momentum factors, for $\mathcal{L}_f$ and $\mathcal{L}_r$.

Recipe 2: Decoupled Statistics in Optimizers

If we use $\widehat{\boldsymbol{g}}_{f,t}$ and $\widehat{\boldsymbol{g}}_{r,t}$ to represent the stochastic gradient from $\mathcal{L}_f$ and $\mathcal{L}_r$ at the time stamp t, respectively.

$$\begin{aligned}
&\text{(Shared Momentum)} \begin{cases} \boldsymbol{m}^S_{f,t} &= \alpha \boldsymbol{m}^S_{r,t-1} + \widehat{\boldsymbol{g}}^S_{f,t}, \quad \theta^S_{f,t} = \theta^S_{r,t-1} - \eta \boldsymbol{m}^S_{f,t} \\ \boldsymbol{m}^S_{r,t} &= \alpha \boldsymbol{m}^S_{f,t} + \widehat{\boldsymbol{g}}^S_{r,t}, \quad \theta^S_{r,t} = \theta^S_{f,t} - \eta \boldsymbol{m}^S_{r,t} \end{cases} \\
&\text{(Decoupled Momentum)} \begin{cases} \boldsymbol{m}^D_{f,t} &= \alpha \boldsymbol{m}^D_{f,t-1} + \widehat{\boldsymbol{g}}^D_{f,t}, \quad \theta^D_{f,t} = \theta^D_{r,t-1} - \eta \boldsymbol{m}^D_{f,t} \\ \boldsymbol{m}^D_{r,t} &= \alpha \boldsymbol{m}^D_{r,t-1} + \widehat{\boldsymbol{g}}^D_{r,t}, \quad \theta^D_{r,t} = \theta^D_{f,t} - \eta \boldsymbol{m}^D_{r,t} \end{cases}
\end{aligned} \tag{1}$$

By induction, the variance of the model parameters by decoupled momentum is *theoretically guaranteed smaller* compared with shared momentum after the same number of iterations.

Theoretical Guarantees

Assumptions:

(Stochastic Gradient Condition) For all time steps $t = 0, \ldots, T-1$, the stochastic gradients of the forget loss $\widehat{\boldsymbol{g}}_{f,t}$ and retain loss $\widehat{\boldsymbol{g}}_{r,t}$ satisfy:

$$\widehat{\boldsymbol{g}}_{f,t} = \boldsymbol{g}_{f,t} + \boldsymbol{\epsilon}_{f,t}, \quad \widehat{\boldsymbol{g}}_{r,t} = \boldsymbol{g}_{r,t} + \boldsymbol{\epsilon}_{r,t},$$

where $\boldsymbol{g}_{f,t} := \nabla_{\theta_t} \mathcal{L}_f(\mathcal{D}_f, \theta_t)$ and $\boldsymbol{g}_{r,t} := \nabla_{\theta_t} \mathcal{L}_r(\mathcal{D}_r, \theta_t)$ are the full-batch gradients with model parameter θ_t at the time stamp t. $\boldsymbol{\epsilon}_{f,t}$ and $\boldsymbol{\epsilon}_{r,t}$ are batch noises with zero mean and a bounded variance: there exists a minimal $\sigma^2 \geq 0$ such that $\mathrm{Var}(\boldsymbol{\epsilon}_{f,t}) \leq \sigma^2$, $\mathrm{Var}(\boldsymbol{\epsilon}_{r,t}) \leq \sigma^2$ for all t.

(Correlation Bounds) The correlation between the stochastic gradients from the same function in different time steps is bounded while the correlation between stochastic gradients from different functions can be ignored. That is to say, $\exists \tau \in [0, 1]$ such that:

$$\forall t_1 \neq t_2, , s.t.\ \rho(\widehat{\boldsymbol{g}}_{f,t_1}, \widehat{\boldsymbol{g}}_{f,t_2}) \leq \tau, \rho(\widehat{\boldsymbol{g}}_{r,t_1}, \widehat{\boldsymbol{g}}_{r,t_2}) \leq \tau, \quad \forall t_1, t_2, \rho(\widehat{\boldsymbol{g}}_{f,t_1}, \widehat{\boldsymbol{g}}_{r,t_2}) \leq o(\tau) \simeq 0$$

(Lipschitz Smoothness) The loss functions $\mathcal{L}_f$ and $\mathcal{L}_r$ are both L-smooth:

$$\forall \theta_1, \theta_2, \|\nabla_{\theta_1} \mathcal{L}_f(\mathcal{D}_f, \theta_1) - \nabla_{\theta_2} \mathcal{L}_f(\mathcal{D}_f, \theta_2)\| \leq L\|\theta_1 - \theta_2\|, \tag{2}$$

$$\forall \theta_1, \theta_2, \|\nabla_{\theta_1} \mathcal{L}_r(\mathcal{D}_r, \theta_1) - \nabla_{\theta_2} \mathcal{L}_r(\mathcal{D}_r, \theta_2)\| \leq L\|\theta_1 - \theta_2\|. \tag{3}$$

Theoretical Guarantees

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Lemma

(Variance of Gradients) If the loss function $\mathcal{L}$ is Lipschitz smooth with a constant L, and $\mathrm{Var}(\theta) \leq \sigma^2_\theta$, then we have $\mathrm{Var}(\nabla_\theta \mathcal{L}(\theta)) \leq L^2\sigma^2_\theta$.

Theorem

(Variance Bound Comparison for Decoupled vs. Shared Momentum) For the shared and decoupled schemes using the same hyperparameters (η, α), and we use $\overline{\mathrm{Var}}(\cdot)$ to denote the maximum variance of a variable, if the function $\mathcal{L}_f$, $\mathcal{L}_r$ and the stochastic gradient $\{(\widehat{\boldsymbol{g}}^S_{f,i}, \widehat{\boldsymbol{g}}^S_{r,i})\}_{i=0}^{T-1}$, $\{(\widehat{\boldsymbol{g}}^D_{f,i}, \widehat{\boldsymbol{g}}^D_{r,i})\}_{i=0}^{T-1}$ satisfy the assumptions, then

$$\forall t, \overline{\mathrm{Var}}(\theta^D_{f,t}) \leq \overline{\mathrm{Var}}(\theta^S_{f,t}), \quad \overline{\mathrm{Var}}(\theta^D_{r,t}) \leq \overline{\mathrm{Var}}(\theta^S_{r,t}),$$

DualOptim

Algorithm 1: Machine Unlearning with Shared Optimizer / Dual Optimizers

```
 1: Input: Model: $f_\theta$; Forget set: $\mathcal{D}_f$; Retain set: $\mathcal{D}_r$; Iterations for outer loop: $T_o$; Iterations for forgetting:
    $T_f$; Iterations for retaining: $T_r$; Step sizes: $\eta$ , $\eta_f$, $\eta_r$ .
 2: $\mathrm{Optim}$ is the same optimizer as in pretraining with step size $\eta$.
    $\mathrm{Optim}_f$ is $\mathrm{Adam}(\theta, \eta_f)$, $\mathrm{Optim}_r$ is the same optimizer as in pretraining with step size $\eta_r$.
 3: for $t = 1, ..., T_o$ do
 4:     for $t' = 1, ..., T_f$ do
 5:         Fetch mini-batch data from the forget set $B_f \sim \mathcal{D}_f$
 6:         Calculate the forget loss $\mathcal{L}_f$ on $B_f$ and get the gradient
 7:         Use $\mathrm{Optim}$ / $\mathrm{Optim}_f$ to update $\theta$
 8:     end for
 9:     for $t' = 1, ..., T_r$ do
10:         Fetch mini-batch data from the retain set $B_r \sim \mathcal{D}_r$
11:         Calculate the retain loss $\mathcal{L}_r$ on $B_r$ and get the gradient
12:         Use $\mathrm{Optim}$ / $\mathrm{Optim}_r$ to update $\theta$
13:     end for
14: end for
15: Output: Model $f_\theta$
```

Experiments: Image Classification

Table 1: Performance summary of MU methods for image classification. Experiments are conducted on (a) 10% random subset of **CIFAR-10** using **ResNet-18** and **(b)** 10% random subset of **TinyImageNet** using **Swin-T**. All results are presented as mean and standard deviation across 5 trials with different random forget data. Performance gaps with *RT* are indicated in blue. The average gap (**Gap**) and average standard deviation (**Std**) metrics are calculated by the average of the gaps and standard deviation measured in FA, RA, TA, and MIA, respectively. All the numbers are in percentage.

(a) **CIFAR-10 Random Subset Unlearning (10%)**

Method	FA	RA	TA	MIA	Gap ↓	Std ↓
RT	94.61$_{\pm 0.46}$ (0.00)	100.00$_{\pm 0.00}$ (0.00)	94.25$_{\pm 0.18}$ (0.00)	76.26$_{\pm 0.54}$ (0.00)	0.00	0.30
FT	99.16$_{\pm 0.10}$ (4.55)	99.84$_{\pm 0.06}$ (0.16)	94.10$_{\pm 0.09}$ (0.15)	88.77$_{\pm 0.38}$ (12.51)	4.34	0.16
GA	98.76$_{\pm 0.39}$ (4.15)	99.10$_{\pm 0.90}$ (0.90)	93.89$_{\pm 0.41}$ (0.36)	92.58$_{\pm 0.55}$ (16.32)	5.43	0.44
RL	97.19$_{\pm 0.21}$ (2.58)	99.67$_{\pm 0.08}$ (0.33)	94.03$_{\pm 0.27}$ (0.22)	68.19$_{\pm 0.95}$ (8.43)	2.80	0.38
SCRUB	92.88$_{\pm 0.25}$ (1.73)	99.62$_{\pm 0.10}$ (0.38)	93.54$_{\pm 0.22}$ (0.71)	82.78$_{\pm 0.86}$ (6.52)	2.33	**0.36**
+DualOptim	94.90$_{\pm 0.42}$ (0.29)	99.52$_{\pm 0.09}$ (0.48)	93.50$_{\pm 0.20}$ (0.75)	78.26$_{\pm 0.79}$ (2.00)	**0.88**	0.38
SalUn	96.99$_{\pm 0.31}$ (2.38)	99.40$_{\pm 0.28}$ (0.60)	93.84$_{\pm 0.36}$ (0.41)	65.76$_{\pm 1.05}$ (10.50)	3.47	0.50
+DualOptim	95.47$_{\pm 0.22}$ (0.86)	99.06$_{\pm 0.94}$ (0.60)	92.47$_{\pm 0.29}$ (1.78)	76.14$_{\pm 0.70}$ (0.12)	**0.93**	**0.35**
SFRon	94.67$_{\pm 3.03}$ (0.06)	99.83$_{\pm 0.13}$ (0.17)	93.98$_{\pm 0.56}$ (0.27)	77.80$_{\pm 5.61}$ (1.54)	0.51	2.33
+DualOptim	94.69$_{\pm 1.13}$ (0.02)	99.92$_{\pm 0.01}$ (0.08)	94.11$_{\pm 0.11}$ (0.14)	77.77$_{\pm 1.39}$ (1.51)	**0.44**	**0.66**

(b) **TinyImageNet Random Subset Unlearning (10%)**

Method	FA	RA	TA	MIA	Gap ↓	Std ↓
RT	85.29$_{\pm 0.09}$ (0.00)	99.55$_{\pm 0.03}$ (0.00)	85.49$_{\pm 0.15}$ (0.00)	69.30$_{\pm 0.20}$ (0.00)	0.00	0.12
FT	96.50$_{\pm 0.10}$ (11.21)	98.23$_{\pm 0.08}$ (1.32)	82.67$_{\pm 0.21}$ (2.82)	79.85$_{\pm 0.13}$ (10.55)	6.48	0.13
GA	90.02$_{\pm 3.26}$ (4.73)	90.84$_{\pm 3.29}$ (8.71)	75.64$_{\pm 2.67}$ (9.85)	78.97$_{\pm 2.07}$ (9.67)	8.24	2.82
RL	94.66$_{\pm 0.26}$ (9.37)	98.02$_{\pm 0.14}$ (1.53)	82.73$_{\pm 0.27}$ (2.76)	54.45$_{\pm 1.04}$ (15.15)	7.13	0.43
SCRUB	97.80$_{\pm 0.16}$ (12.51)	98.13$_{\pm 0.08}$ (1.42)	82.64$_{\pm 0.19}$ (2.85)	79.62$_{\pm 0.41}$ (10.32)	6.78	**0.21**
+DualOptim	97.20$_{\pm 0.20}$ (11.91)	98.30$_{\pm 0.10}$ (1.25)	83.17$_{\pm 0.19}$ (2.32)	79.10$_{\pm 0.63}$ (9.80)	**6.32**	0.28
SalUn	97.69$_{\pm 0.14}$ (12.40)	98.89$_{\pm 0.03}$ (0.66)	84.02$_{\pm 0.32}$ (1.47)	61.87$_{\pm 0.97}$ (7.43)	5.49	0.37
+DualOptim	91.68$_{\pm 0.28}$ (6.39)	95.13$_{\pm 0.18}$ (4.42)	80.16$_{\pm 0.34}$ (5.33)	72.48$_{\pm 0.33}$ (3.18)	**4.83**	**0.28**
SFRon	96.41$_{\pm 0.74}$ (11.12)	98.95$_{\pm 0.22}$ (0.60)	83.40$_{\pm 0.51}$ (2.09)	70.40$_{\pm 3.15}$ (1.10)	3.73	1.16
+DualOptim	92.26$_{\pm 1.44}$ (6.97)	98.27$_{\pm 0.12}$ (1.28)	83.12$_{\pm 0.21}$ (2.37)	69.19$_{\pm 2.27}$ (0.11)	**2.68**	**1.01**

Experiments: Image Generation

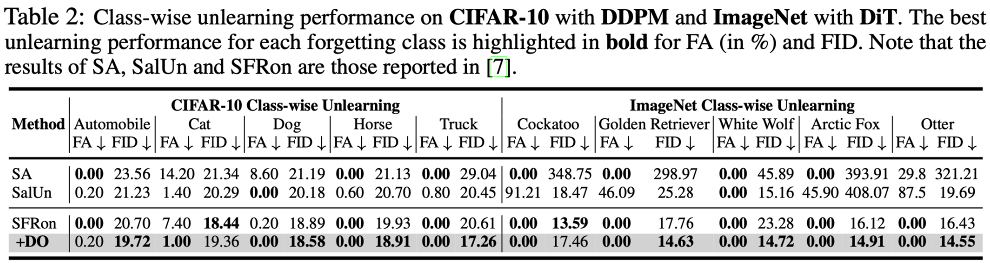

Table 2: Class-wise unlearning performance on **CIFAR-10** with **DDPM** and **ImageNet** with **DiT**. The best unlearning performance for each forgetting class is highlighted in **bold** for FA (in %) and FID. Note that the results of SA, SalUn and SFRon are those reported in [7].

Method	**CIFAR-10 Class-wise Unlearning**										**ImageNet Class-wise Unlearning**									
	Automobile		Cat		Dog		Horse		Truck		Cockatoo		Golden Retriever		White Wolf		Arctic Fox		Otter	
	FA ↓	FID ↓	FA ↓	FID ↓	FA ↓	FID ↓	FA ↓	FID ↓	FA ↓	FID ↓	FA ↓	FID ↓	FA ↓	FID ↓	FA ↓	FID ↓	FA ↓	FID ↓	FA ↓	FID ↓
SA	**0.00**	23.56	14.20	21.34	8.60	21.19	**0.00**	21.13	**0.00**	29.04	**0.00**	348.75	**0.00**	298.97	**0.00**	45.89	**0.00**	393.91	29.8	321.21
SalUn	0.20	21.23	1.40	20.29	**0.00**	20.18	0.60	20.70	0.80	20.45	91.21	18.47	46.09	25.28	**0.00**	15.16	45.90	408.07	87.5	19.69
SFRon	**0.00**	20.70	7.40	**18.44**	0.20	18.89	**0.00**	19.93	**0.00**	20.61	**0.00**	**13.59**	**0.00**	17.76	**0.00**	23.28	**0.00**	16.12	**0.00**	16.43
+DO	0.20	**19.72**	**1.00**	19.36	**0.00**	**18.58**	**0.00**	**18.91**	**0.00**	**17.26**	**0.00**	17.46	**0.00**	**14.63**	**0.00**	**14.72**	**0.00**	**14.91**	**0.00**	**14.55**

Experiments: Large Language Models

Table 4: Performance comparison of different MU methods on TOFU-finetuned **Phi-1.5** and **LLaMA 2**. The results include Model Capability (MC), Forget Efficacy (FE), and the average metric (Avg.) for forget 1%, 5% data, and 10% data.

Method	**Phi-1.5**									**LLaMA 2**								
	forget 1% data			forget 5% data			forget 10% data			forget 1% data			forget 5% data			forget 10% data		
	MC ↑	FE ↑	Avg. ↑	MC ↑	FE ↑	Avg. ↑	MC↑	FE ↑	Avg. ↑	MC ↑	FE ↑	Avg. ↑	MC ↑	FE ↑	Avg. ↑	MC ↑	FE ↑	Avg. ↑
GA+GD	0.4934	0.4493	0.4714	0.4360	0.5084	0.4722	0.4471	0.5246	0.4859	0.6696	0.5908	0.6302	0.0000	0.8772	0.4386	0.5592	0.9346	0.7469
ME+GD	**0.4944**	0.3938	0.4441	0.4559	0.4480	0.4520	0.4594	0.4564	0.4579	0.7271	0.9204	0.8237	**0.7472**	0.9313	0.8392	**0.7357**	0.9489	0.8423
+DO	0.4866	**0.6913**	**0.5889**	**0.4676**	**0.8200**	**0.6438**	**0.5009**	**0.7732**	**0.6370**	**0.7425**	**0.9612**	**0.8519**	0.7316	**0.9602**	**0.8459**	0.7315	**0.9625**	**0.8470**
DPO+GD	0.2410	0.6831	0.4621	0.4105	0.6334	0.5219	0.3517	0.6302	0.4910	0.7564	0.5335	0.6450	0.0000	0.8243	0.4122	0.0000	0.8041	0.4021
IDK+AP	**0.4403**	0.5723	0.5063	**0.4800**	0.5112	0.4956	**0.4614**	0.6003	0.5308	**0.7580**	0.7625	0.7603	**0.7529**	0.7479	0.7504	**0.7471**	0.7433	0.7452
+DO	0.4221	**0.7037**	**0.5629**	0.4633	**0.6974**	**0.5804**	0.4422	**0.7193**	**0.5807**	0.7412	**0.8075**	**0.7743**	0.7354	**0.7958**	**0.7656**	0.7362	**0.7855**	**0.7609**

Thank You!