Partially Blinded Unlearning

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Table of Contents: Partially Blinded Unlearning

1. Machine Unlearning
2. Research Objective and Problem Formulation
3. Proposed Methodology
4. Experiments and Results
5. Conclusion and Future works

1 Machine Unlearning

2 Research Objective and Problem Formulation

3 Proposed Methodology

4 Experiments and Results

5 Conclusion and Future works

Machine Unlearning

- What is Machine Unlearning?
  - machine unlearning refers to the task of forgetting the learned information or erasing the influence of a specific data subset of the training dataset from a learned model in response to a user request.
- What are the Mathematical Definitions?
  - Z as an example space, i.e., a space of datasets.
  - Given a dataset D, we want to obtain a machine-learning model from a hypothesis space H. The process of training a model on D by a learning algorithm, denoted by a function $A : Z \to H$, with the trained model denoted as $A(D)$.
  - To support forgetting requests, an unlearning mechanism, denoted by a function U, that takes as input a training dataset $D \in Z$, a forget set $D_f \subset D$ (data to forget), and a model $A(D)$. It returns a sanitized (or unlearned) model $U(D, D_f, A(D)) \in H$.
  - The unlearned model is expected to be the same or similar to a retrained model $A(D \setminus D_f)$

1 Machine Unlearning

2 Research Objective and Problem Formulation

3 Proposed Methodology

4 Experiments and Results

5 Conclusion and Future works

Research Objective and Problem Formulation

- **Objectives**
  1. Formulate a methodology aimed for forgetting information linked to a specific class of data from a pre-trained classification network.
  2. Decrease model's performance on the unlearned data class while minimizing any detrimental impacts on the model's performance in other classes.

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- **Objectives**
  1. Formulate a methodology aimed for forgetting information linked to a specific class of data from a pre-trained classification network.
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- **Formulation**
  1. parameter space $\Theta \subseteq R^m$. Pre-trained classification model denoted as f_{θ^*} with initial parameters $\theta^* \in \Theta$. Trained using a dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{|\mathcal{D}|}$, where $(x_i, y_i) \overset{iid}{\sim} P_{XY}(x, y)$. the label space $\mathcal{Y} = \{0, 1, 2, \ldots, C-1\}$
  2. a particular class or classes of data points $s_n \in \mathcal{Y}$ that the model needs to unlearn. So unlearning samples of that specific class denoted as $\mathcal{S}_n = \{(x_i, y_i) : y_i = s_n\}$. The objective of unlearning is to determine a parameter θ^u for the unlearned model f_{θ^u} that closely aligns with the performance of the retrained model f_{θ^p} trained on samples $\mathcal{S}_p = \mathcal{D} \setminus \mathcal{S}_n$.

1 Machine Unlearning

2 Research Objective and Problem Formulation

3 Proposed Methodology

4 Experiments and Results

5 Conclusion and Future works

Proposed Methodology

1. Given θ^* and $\mathcal{S}_n$, the unlearning objective find $\theta^p = \arg\max_\theta P(\theta|\mathcal{S}_p)$

$$\theta^p = \arg\max_\theta \log P(\theta|\mathcal{S}_p) \tag{1}$$
$$= \arg\max_\theta \log P(\mathcal{S}_p|\theta) + \log P(\theta) - \log P(\mathcal{S}_p) \tag{2}$$
$$= \arg\max_\theta \log P(\mathcal{S}_p|\theta) + \log P(\theta) - K_1 \tag{3}$$

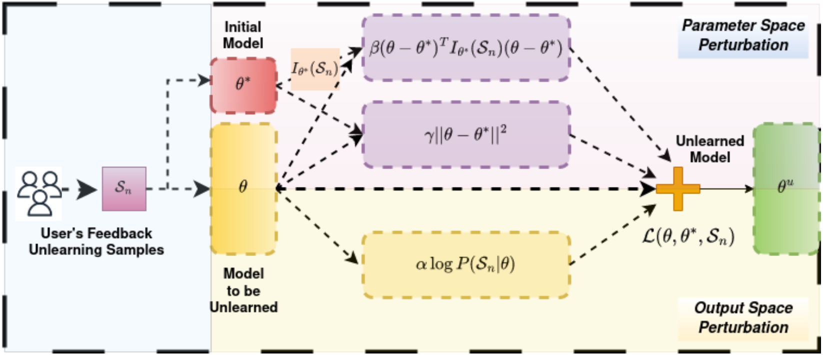
$$\log P(\theta|\mathcal{D}) = \log P(\theta|\mathcal{S}_p, \mathcal{S}_n) \tag{4}$$
$$= \log P(\mathcal{S}_p, \mathcal{S}_n|\theta) + \log P(\theta) - K_2 \tag{5}$$
$$= \log P(\mathcal{S}_p|\theta) + \log P(\mathcal{S}_n|\theta) + \log P(\theta) - K_2 \tag{6}$$

2. Now using the substituting the value of $\log P(\mathcal{S}_p|\theta) + \log P(\theta)$

$$\theta^p = \arg\max_\theta \log P(\theta|\mathcal{D}) - \log P(\mathcal{S}_n|\theta) + K_2 - K_1 \tag{7}$$
$$= \arg\max_\theta \mathcal{L}(\theta, \mathcal{D}, \mathcal{S}_n) \tag{8}$$

Proposed Methodology

$$\mathcal{L}(\theta, \theta^*, \mathcal{S}_n) \approx \alpha \log P(\mathcal{S}_n|\theta) + \beta(\theta - \theta^*)^T I_{\theta^*}(\mathcal{S}_n)(\theta - \theta^*) + \gamma||\theta - \theta^*||^2 \quad (9)$$



1 Machine Unlearning

2 Research Objective and Problem Formulation

3 Proposed Methodology

4 Experiments and Results

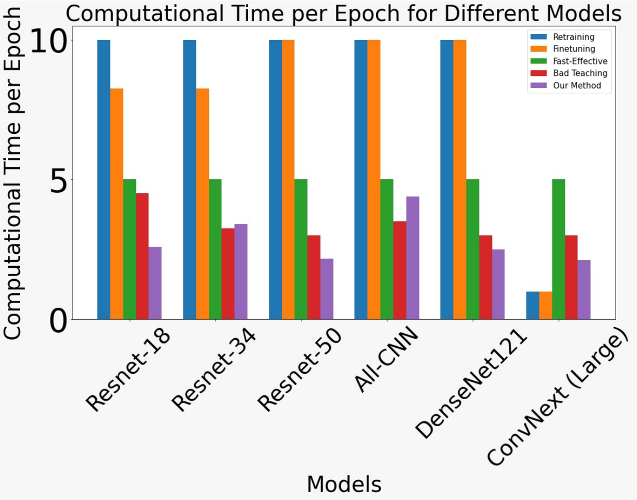
5 Conclusion and Future works

Experiments and Results

Table: accuracy on the forgotten class: $A_{D_f}(\%)$ and accuracy on the remaining classes: $A_{D_r}(\%)$

Dataset	Models	Classes	Initial Training		Re-training		Fine-tuning		Fast-Effective [?]		Bad Teaching [?]		Our Method(PBU)	
			A_{D_f}	A_{D_r}	A_{D_f}	A_{D_r}	A_{D_f}	A_{D_r}	A_{D_f}	A_{D_r}	A_{D_f}	A_{D_r}	A_{D_f}	A_{D_r}
MNIST	**Resnet-34**	Class-2	99.65±0.11	99.42±0.11	0±0	99.33±0.11	0±0	99.37±0.06	0±0	94.17±0.88	0±0	97.96±0.29	**0.03±0.06**	**98.73±0.57**
		Class-6	98.89±0.59	99.51±0.06	0±0	99.34±0.14	0±0	99.44±0.16	0±0	89.13±2.86	0±0	87.62±0.49	**0±0**	**91.09±2.9**
		Class-8	99.73±0.21	99.41±0.12	0±0	99.31±0.08	0±0	99.37±0.19	0±0	94.64±1.97	0±0	96.18±0.53	**0±0**	**98.24±0.36**
	Densenet-121	Class-2	99.6±0.12	99.44±0.11	0±0	99.15±0.05	0±0	99.37±0.12	0±0	91.43±1.62	0±0	94.15±0.54	**0±0**	**96.5±0.3**
		Class-6	99.72±0.12	99.53±0.1	0±0	99.29±0.05	0±0	99.69±0.16	0±0	96.1±0.65	0±0	97.97±0.23	**0.84±0.35**	**98.65±0.11**
		Class-8	98.95±0.63	99.58±0.11	0±0	99.47±0.09	0±0	99.53±0.08	0±0	94.5±2.34	0±0	94.83±0.59	**0.27±0.24**	**98.57±0.31**
	ConvNeXt-L	Class-2	99.69±0.21	99.55±0.1	0±0	99.11±0.1	0±0	99.19±0.12	0.18±0	97.52±0.24	0±0	97.18±1.14	**0±0**	**98.65±0.29**
		Class-6	99.05±0.05	99.59±0.1	0±0	98.83±0.17	0±0	98.63±0.01	0±0	98.25±0.13	0±0	97.75±0.51	1±0.16	**98.33±0.18**
		Class-8	99.56±0.06	99.6±0.14	0±0	98.81±0.06	0±0	98.85±0.04	0±0	97.54±0.99	0±0	96.51±1.5	1.22±1.56	**97.26±1.59**
CIFAR-100	**Resnet-50**	Class-1	86.33±7.23	75.87±0.31	0±0	75.2±0.34	0±0	69.98±1.24	0±0	54.61±0.21	0.87±0.23	68.06±0.14	**0±1.15**	**70.51±0.18**
		Class-3	56.67±11.72	76.17±0.41	0±0	74.12±0.93	0±0	69.25±0.36	0±0	59.43±0.56	0±0	70.35±1.19	**0.5±0.58**	**71.85±0.91**
		Class-8	92.33±2.89	75.81±0.34	0±0	74.31±0.83	0±0	68.28±0.66	0±0	57±0.1	**0±0**	**65.98±0.78**	0.5±1	65.51±2.05
	Densenet-121	Class-1	56.33±4.93	74.65±1.42	0±0	74.18±2.47	0±0	74.55±0.66	0±0	50.75±2.77	0±0	51.83±1.25	**0.5±0.58**	**63.96±1.37**
		Class-3	89.8±1.31	74.74±1.83	0±0	73.9±2.32	0±0	74.54±1.88	0±0	56.84±3.41	1.31±1.15	54.52±3.03	**0.15±0.17**	**66.38±3.65**
		Class-8	74.78±23.81	75.51±2.85	0±0	72.29±2.39	0±0	75.1±1.27	0±0	52.88±1.44	0.18±0.31	56.61±2.06	**0.4±0.46**	**64.6±3.51**
	ConvNeXt-L	Class-1	91.59±4.13	89.03±1.03	0±0	73.03±0.55	0±0	73.79±0.17	0±0	75.25±1.01	0±0	72.26±1.07	1.9±0.85	**76.82±1.19**
		Class-3	77.47±1.86	88.59±1.09	0±0	73.15±0.3	0±0	74.95±0.16	0±0	70.51±0.65	0±0	71±0.39	1±1.15	**72.51±1.12**
		Class-8	99.41±0.86	89.22±1.03	0±0	71.83±0.35	0±0	73.65±1.19	0±0	71.22±0.93	0±0	71.97±0.26	**0±0.18**	**72.64±0.23**
FOOD-101	**Resnet-50**	Class-10	67.2±5.54	78.18±0.01	0±0	75.1±0.23	0±0	77.3±0.77	0±0	60.83±1.4	0±0	56.07±1.08	**0.8±0.69**	**68.34±1.24**
		Class-30	90.8±4.16	77.94±0.01	0±0	74.86±0.09	0±0	77.08±0.25	0±0	62.13±0.95	0±0	52.45±0.57	**0.27±0.46**	**65.46±0.32**
		Class-50	59.6±4.85	78.26±0	0±0	74.18±0.2	0±0	77.23±0.32	0±0	63.06±0.77	0±0	55.53±0.48	**0±0**	**69.43±0.81**
	Densenet-121	Class-10	60.87±6.31	75.85±1.93	0±0	75.38±0.61	0±0	75.65±1.12	0±0	53.5±1.89	0±0	50.91±0.37	1.2±1.31	**64.97±2**
		Class-30	88.13±0.46	76.17±0.74	0±0	74.91±1.53	0±0	75.37±1.59	0±0	57.8±1.1	0.87±1.15	54.86±1.84	**0.67±0.86**	**64.75±2**
		Class-50	58.05±13.76	77.67±1.88	0±0	75.24±0.55	0±0	75.7±1.05	0±0	55.56±4.65	0.29±0.27	58.23±0.77	**0±0**	**67.9±2**
	ConvNeXt-L	Class-20	90.38±0.76	87.43±0.59	0±0	87.73±0.62	0±0	88.51±0.53	0±0	69.26±0.92	0±0	68.77±0.41	**0±0**	**75.97±0.79**
		Class-40	96.35±0.74	87.17±0.37	0±0	87.02±0.17	0±0	88.46±0.2	0±0	72.37±1.76	0±0	70.62±0.28	**0±0**	**78.45±0.79**
		Class-60	93.41±0.72	86.45±0.55	0±0	86.83±0.34	0±0	87.44±0.28	0±0	73.05±1.6	0±0	73.83±0.39	**0.74±0.5**	**81.79±0.99**

Experiments and Resutls



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5. Conclusion and Future works

Conclusion and Future works

- A novel method tailored for unlearning specific classes within deep classification models. A key distinguishing feature of our approach is its capability to function effectively even with partial access only to the unlearning class data
- As part of future work a slight extension of this method is now being investigated for applying unlearning in diffusion models.