Vertical Machine Unlearning: Selectively Removing Sensitive Information From Latent Feature Space

Tao Guo, Song Guo, Jiewei Zhang, Wenchao Xu, Junxiao Wang
Department of Computing, The Hong Kong Polytechnic University, Hong Kong, China

Abstract

Recently, the enactment of privacy regulations has promoted the rise of machine unlearning paradigm. Most existing studies mainly focus on removing unwanted data samples from a learnt model. Yet we argue that they remove overmuch information of data samples from latent feature space, which is far beyond the sensitive feature scope that genuinely needs to be unlearned. In this paper, we investigate a vertical unlearning mode, aiming at removing only sensitive information from latent feature space. First, we introduce intuitive and formal definitions for this unlearning and show its orthogonal relationship with existing horizontal unlearning. Secondly, given the fact of lacking general solutions to vertical unlearning, we introduce a ground-breaking solution based on representation detachment, where the task-related information is encouraged to retain while the sensitive information is progressively forgotten. Thirdly, observing that some computation results during representation detachment are hard to obtain in practice, we propose an approximation with an upper bound to estimate it, with rigorous theoretical analysis. We validate our method by spanning several datasets and models with prevailing performance. We envision this work as a necessity for future machine unlearning system and a essential component of the latest privacy-related legislation.

1 Introduction

The progressive utilization of personal data has contributed to a wide spectrum of applications in intelligent healthcare, smart finance and secure access, etc. To prevent potential leakage and illegal use of private data, collaborative machine learning paradigms are proposed to train models without sharing users’ data, e.g., federated learning [Yang et al., 2019], split learning [Vepakomma et al., 2018]. However, the models trained from isolated data may still have memories of them, leading to growing concerns of exposing sensitive information from existing trained models, such as diagnosis records, bank statement, facial images, etc.

Recently, laws and regulations are enforced for companies and organizations on ‘reasonable use of personal data’, e.g., the European Union’s General Data Protection Regulation (GDPR) [Mantelero, 2013] and the California Consumer Privacy Act (CCPA) [Legislation, 2018], which allow people to get more control on their own data, and deliberately emphasis on the right to be forgotten. Thus implementations to eliminate any unwanted personal information contained on trained models are extensively called for [Bourtoule et al., 2021].

Under such circumstance, machine unlearning mechanisms are researched to remove the knowledge learned from the data that need to be forgotten, which aims at eliminating the contribution from some private data samples [Ginart et al., 2019; Cao and Yang, 2015; Bourtoule et al., 2021; Huang et al., 2021]. Although these studies have shown effectiveness in forgetting personal data that users want to erase, there are some challenges to ensure the the right to be forgotten while maintaining the model performance and satisfying the diverse user demands at the same time. First, some key feature information that contribute to the model accuracy may be unlearned. As the volume of data samples ought to delete become larger, the model performance may suffer from sudden deterioration. Secondly, since the whole contribution of a data point is eliminated, it is difficult for existing methods to unlearn a certain feature while retaining the others, e.g., gender information, particular health index, etc. In addition, if a certain feature is required to be removed from a model for all users, it is difficult for current methods to search an effective subset of data to conduct the unlearning process.

Such challenges come from the limitation of existing machine unlearning methods that only consider the data sample space while ignore the key latent feature space. For example, the survival predictive model of patients could be used for unwanted purposes, e.g., profitable target social advertising. It should be adequate to just remove the social feature information rather then the whole knowledge learned from the data samples [Vepakomma et al., 2018]. Also, face recognition model may require to explicitly forget some sensitive information like gender or ethnicity to avoid discrimination or misuse [Morales et al., 2020]. The choice we face is thus either to unlearn data samples that some users require to delete (which retains vulnerable features), or eliminating all learned knowledge for a feature (which loses model accuracy).
To deal with the above dilemma, we consider an orthogonal unlearning mode dubbed 'vertical machine unlearning' that targets on erasing certain feature information. As shown in Fig. 1, status quo mechanisms are classified as 'horizontal machine unlearning', where data samples are listed in horizontal dimension, while features are listed in vertical dimension. To the best of our knowledge, we are the first to bring up this concept to explicitly unlearn sensitive features of a machine learning model. We envision this work as an important complementary block towards the machine unlearning for a variety of model security requirements. The contribution of the paper is summarized as follows:

- We define and introduce a novel machine unlearning category, namely, vertical unlearning, into nowadays machine unlearning system. Vertical unlearning aims at unlearning selected sensitive information in the latent feature space from trained models, which is from an orthogonal perspective comparing with traditional machine unlearning ways that erase the user data sample.

- A general vertical unlearning method is proposed via a representation detachment based method to selectively removing sensitive information-related representation, e.g., gender, ethnicity from task-related representation, which are eventually eliminated from the model.

- To deal with the difficulties in calculating the mutual information required in vertical unlearning, we propose an approximation method with rigorous theoretical analysis and negligible deviation.

- Extensive experiments are conducted and shown the effectiveness and performance of our proposed vertical unlearning methods.

2 Preliminaries

For sake of completeness, we briefly review current emerging data privacy legislation, existing machine unlearning researches and our interpretation for future machine unlearning.

2.1 Data Privacy Legislation

The rapid development of Big Data boosts the advancement of Deep Learning by utilizing a massive amount of data generated from different sources across a wide range of sectors, such as healthcare and finance. Yet the risk of privacy violation increases as we savoring the benefits of 'free' data. To address the privacy issue, numbers of privacy-preserving mechanisms [Mehmood et al., 2016; Papernot et al., 2016; Liu et al., 2021] emerge for privacy protection at different stages from data generation to data processing. Furthermore, privacy regulation [Mantelero, 2013; Legislation, 2018; Garcia et al., 2020; De Bruyn, 2014] has been introduced to legitimize and protect sensitive information against hackers and leaks to make our digital environment safer and more secure. However, more and more emerging legislation emphasizes customers’ rights other than merely keeping data safe from unauthorized access. Customers have rights to control their usage permission of their information and the for what purpose.

2.2 Current Machine Unlearning Methods

Recently, another branch of privacy-preserving Machine Learning arised, called Machine Unlearning [Cao and Yang, 2015; Bourtoule et al., 2021], which is brought to address the challenges of unlearning required data samples from a learnt model without compromising previous model performance. Since the existing techniques focus on the perspective from horizontal dimension, i.e., data samples space, we define it as horizontal unlearning. [Cao and Yang, 2015] first introduced the term "Machine Unlearning" and proposed an possible way to solve it. After that, [Bourtoule et al., 2021] proposed a sharding-based strategy leveraging ensemble learning and distributed manner, which establish a general method and a new baseline for further research. Later studies either focus on the different algorithms or minimizing computational and storage complexity in this area [Huang et al., 2021; Sekhari et al., 2021; Gupta et al., 2021; Brophy and Lowd, 2021].

2.3 Interpretation for future Machine Unlearning

Emergent privacy protection not only focus on protecting data from unauthorized access, but also concerning subjective intention of how their data be used and what the purpose of utilization. Most of the studies have an eye on addressing this issue by unlearning data samples from the learnt model, however, such action only handles the problem from data space level and might severely influence the model performance especially when the data samples that required to be deleted enlarging. We interpret the machine unlearning from the orthogonal perspective, i.e., to eliminating personal information from latent feature space in the vertical direction. This particular thoughts can either satisfy the protection of certain sensitive features, e.g., gender, ethnicity, but also retain the contribution to the model learned from these data samples.

3 Define Vertical Machine Unlearning

In this section, we define the concept of Vertical Machine Unlearning, then we show the architecture of Horizontal Machine Unlearning and Vertical Machine Unlearning and summarize their different focuses in real world scenarios.

Suppose we have \( n \) users with \( k \) features. let \( D = \{d_1, d_2, \ldots, d_n\} \) be dataset space that model train on and \( F = \{f_1, f_2, \ldots, f_k\} \) be the latent feature space that data space can mapping to, \( \phi \) be the model in hypothesis space after training.
**Definition 3.1 (Vertical Machine Unlearning).** We define the algorithm $L: F \rightarrow \phi$ be a learning process which maps latent feature space $F$ into the hypothesis space of model $\phi$. $f_i$ be the latent feature that user $i$ requires to delete. We define a unlearning process $U: L(F) \otimes F \otimes f_i \rightarrow \phi$, which takes an input latent feature space $F$, a learnt model $L(F)$ and the feature $f_i$ that required to be forgotten. Thus the objective of Vertical Machine Unlearning can be described as
\[
P( L(F \setminus f_i)) = P( U(L(F), F, f_i)),
\]
where $F \setminus f_i$ defines the latent feature space without selective sensitive feature $f_i$. $P(.)$ indicates to have the identical probabilities for each models.

We also depict the architecture of horizontal learning and vertical learning in Fig. 1 to better understand the difference between the two modes. We can see from the figure that the horizontal axis represents the samples, the vertical axis represents features and each sample contains several latent features inside the data. The comparison manifests the intrinsic differences between them is that the horizontal unlearning aiming to unlearn models by deleting certain data samples while vertical unlearning targets on the features.

## 4 Vertical Machine Unlearning with Representation Detachment

Unlike data samples, depriving features is not easy since they are embedded over the entire datasets. To fully realize the purpose of selectively unlearning sensitive features, we introduce Representation Disentanglement which based on Mutual Information in our method. We first introduce the Mutual Information and then elaborate the proposed Representation Detachment approach which gradually eliminate the undesirable sensitive information during the training procedure. Finally, we introduce the Representation Detachment Loss we use in the training process.

### 4.1 Mutual Information

Mutual Information serves as an evaluation criteria as a measure of mutual dependence between the two variable in the probability or information theory. And in Machine Learning Field, Mutual Information is linked to the entropy of a random variable and quantify the expected ‘amount of information’ in a given variable [Batina et al., 2011; Gierlichs et al., 2008]. So that Mutual Information are used in algorithm like Decision Tree as feature selector or embedded in loss function to detect and evaluate the dependency between variables.

### 4.2 Representation Detachment

The overall architecture of our unlearning process is designed to gradually remove sensitive information from trained model with Representation Detachment, which is shown in Fig. 2.

**Training Procedure** During the training phase, we employ the Representation Detachment Loss to filtrate sensitive information act on the intermediate model output. According to some recent findings several model interpretation researches [Ren et al., 2021; Li et al., 2021] explores, intermittent feature of lower complexity orders represent more general information, while that of higher complexity orders gives more noises. According to this precise discover, we choose to process the feature of the middling complexity orders, in our case, intermediate output of model from the middle range layers.

As input data $x$ pass through the first few layers in generating intermediate feature maps, two branches are separated, one of the branches flows to the small auxiliary network, where feature separation operates. For the other branch, intermediate features will transmit and pass through later parts of model for parameters update to achieve a higher accuracy for task prediction. To achieve the final purpose, we are encouraged to separate task-related information from background nuisance as well as sensitive information, e.g., gender, ethnicity, simultaneously. So we design a Representation Detachment Loss $L_{infoDetach}$ to help feature separation, which will be elaborated in the following section.

**Asynchronous Acceleration** To counteract the side-effect we bring in the unlearning procedure, local update is used to facilitate training process. Other than updating parameters in a end-to-end paradigm, which can cause a serious delay due to the sequential order of backward propagation behavior, local updating we use will bring parallelism in to the training and accelerate the process. Auxiliary Network with $L_{infoDetach}$ can be viewed as a small classifier and perform with final classifier for simultaneous back propagation. In this way, the whole training process can be more efficient with its natural architecture advantage.

### 4.3 Representation Detachment Loss

In this section, we introduce the Representation Detachment we proposed during training in selectively removing sensitive information from the learnt model. The loss function is given by
\[
L_{infoDetach} = \alpha(-I(h, x) + \beta I(h, r^s) + \gamma I(h, s^a))
\]
where $I(a, b)$ represent the mutual information between $a$ and $b$. As we review from the previous section, $s$ and $r$ represent sensitive and irrelevant information related to identification, and since we are unable to capture all the information in practice, we use $s^a$ and $r^s$ instead to express the information we captured through training. Also, $y$ represents non-sensitive information related to identification and $x$ refer to the raw input. Thus here we have
\[
\begin{align*}
    r^s &= \text{argmax}_{r, I(r, x)>0, I(r, y)=0} I(h, r), \\
    s^a &= \text{argmax}_{s, I(s, x)>0, I(s, y)=0} I(h, s),
\end{align*}
\]

Now that Three additive terms are introduced in (2), we are here to elaborate the purpose of each term. $I(h, x)$ is used to capture the mutual information between intermediate feature and input image, the more the better. $I(h, r^s)$ is used to extract the mutual information between intermediate feature with task-irrelevant nuisance, like background, which serves as the purpose of improving accuracy. And the last term $I(h, s^a)$ aims to extract the mutual information between intermediate feature with selected sensitive feature, which is the main process of unlearning features. Obviously, $r$, $y$ and $s$ are independent of each other. Combining the three components we will be able to to discard sensitive and irrelevant
information and in the meantime retain task-relevant information which contribute to the final classification, by minimizing the function (2).

5 Approximate Disentanglement
Since $I(h, r^*)$ and $I(h, s^*)$ are difficult to calculate in practice, we use the upper bound of the function (2) to approximate the loss. Our result is in the Proposition 1, with the detailed proof below. For convenience, we will omit the subscript of loss in the following part.

**Proposition 1.** Suppose that the Markov chain $(y, r, s) \rightarrow x \rightarrow h$ holds. Then the upper bound of $\mathcal{L}$ is as follows

$$
\mathcal{L} \leq -\lambda_1 I(h, x) - \lambda_2 I(h, y) - \lambda_3 I(h, z) = \overline{\mathcal{L}}
$$

where $\lambda_1 = \alpha(1 - \beta)$, $\lambda_2 = \alpha \beta$, $\lambda_3 = \alpha(\beta - \gamma)$, $\beta \geq \gamma$, and $z$ represent the sensitive attribute.

Suppose $\gamma > \beta$, the blur of the sensitive information possibly contains much information critical to the recognition, which would degrade the recognition accuracy. We intend to conceal the sensitive information instead of devastating the recognition. Compared with the level of removing the background or irrelevant information, the blur degree of sensitive information should be mild.

To guarantee the accuracy of approximation, the gap between $\mathcal{L}$ and $\overline{\mathcal{L}}$ should be small. We present a bound of the gap in the Proposition 2.

**Proposition 2.** Assume that there exists a deterministic function map $x \rightarrow y$, the gap $\epsilon = \overline{\mathcal{L}} - \mathcal{L}$ can be bounded by

$$
\epsilon \leq \alpha \beta (I(x, y) - I(h, y) - I(h, z))
$$

According to the conclusion of mutual information estimation [Wang et al., 2021], we can calculate $I(h, x)$ by $R_{a}(x|h)$ which is the expected error for reconstructing $x$ from $h$, and as for $I(h, y)$, $I(h, z)$, we can train auxiliary classifiers $q_{\psi_1}(y|h), q_{\psi_2}(z|h)$ to approximate.

5.1 PROOF OF PROPOSITION 1
Proof. Note that, our original loss function is given by

$$
\mathcal{L} = \alpha (-I(h, x) + \beta I(h, r^*) + \gamma I(h, s^*))
$$

where $\alpha, \beta, \gamma \geq 0$. Since the Markov chain $(y, r, s) \rightarrow x \rightarrow h$, we have the following inequality

$$
I(h, (y, r^*, s^*)) \leq I(h, x)
$$

Given that

$$
I(h, (y, r^*, s^*)) = H(h) - H(h|r^*) + H(h|r^*) - H(h|y, r^*, s^*) = I(h, r^*) + I(h, (y, s^*)|r^*)
$$

Where $H(\cdot)$ represents information entropy and mutual information has the property that $I(a, b) = H(a) - H(a|b)$. Considering that $y, r^*$ and $s^*$ are independent of each other, and the property of mutual information $I(a, b) = I(b, a)$, then

$$
I(h, (y, s^*)|r^*) \geq H(y, s^*) - H(y, s^*)|h]
$$

$$
= I(h, s^*) + I(y|s^*) - H(y|h, s^*) \geq I(h, s^*) + I(h, y)
$$

Combining the equation 8 and the inequality 7, 9, we can get the following inequality

$$
I(h, (y, r^*, s^*)) \leq I(h, x) - I(h, y)
$$

So we can eliminate $I(h, r^*)$ in the original loss function that are hard to calculate.

$$
\mathcal{L} \leq \alpha (-I(h, x) + \beta (I(h, x) - I(h, y)) + p)
$$

Where $p = (\gamma - \beta)I(h, s^*)$. Then our target is to find the bound for $p$. We can deduce sensitive information from sensitive attributes. There is another Markov chain $z \rightarrow s$. Then $I(h, z) \leq I(h, s^*)$. Combining the assumption $\beta \geq \gamma$, we can get $p \leq (\gamma - \beta)I(h, z)$. We have already discussed the necessity of $\beta \geq \gamma$ in the text. So we can prove that

$$
\mathcal{L} \leq -\lambda_1 I(h, x) - \lambda_2 I(h, y) - \lambda_3 I(h, z)
$$

where $\lambda_1 = \alpha(1 - \beta)$, $\lambda_2 = \alpha \beta$, $\lambda_3 = \alpha(\beta - \gamma)$.

Figure 2: **Vertical unlearning architecture of Representation Detachment**: We depict the whole process of vertical unlearning and show the separation of different features by Representation Detachment Loss.
We can easily generalize this proposition to the multi-attribute case.

\[
L \leq -\lambda_1 I(h, x) - \lambda_2 I(h, y) - \sum_{i=1}^{n} \sigma_i I(h, z_i) \tag{13}
\]

where \( L = \alpha(-I(h, x) + \beta I(h, r^*) + \sum \gamma_i I(h, s_i^*)) \), \( \lambda_1 = \alpha(1 - \beta) \), \( \lambda_2 = \alpha \beta \), \( \sigma_i = \alpha(\beta - \gamma_i) \).

### 5.2 PROOF OF PROPOSITION 2

**Proof.** The gap \( \varepsilon \) is given by

\[
\varepsilon = \alpha(\beta Q_1 + \gamma Q_2 - \beta I(h, z)) \tag{14}
\]

where \( Q_1 = I(h, x) - I(h, y) - I(h, r^*) \), \( Q_2 = I(h, z) - I(h, s^*) \). Suppose there is a function \( f \) make that \( x = f(y, r, s) \). Let \( \tilde{r} \) and \( \tilde{s} \) be the random variable in the function \( f \). We have

\[
I(h, x) = I(h, (y, \tilde{r}, \tilde{s})) \tag{15}
\]

Obviously, \( I(h, \tilde{r}) \leq I(h, r^*) \). We obtain

\[
Q_1 \leq I(h, x) - I(h, y) - I(h, \tilde{r}) = I(h, \tilde{r}) + I(h, (y, \tilde{s})|\tilde{r}) - I(h, y) - I(h, \tilde{r})
\]

\[
= I(h, (y, \tilde{s})|\tilde{r}) - I(y, x) + I(x, y) - I(h, y)
\]

\[
= H((y, \tilde{s})|\tilde{r}) - H(y, \tilde{s}|h, \tilde{r}) - H(y) + H(y|x)
\]

\[
+ I(x, y) - I(h, y) \tag{16}
\]

Given that \( y, \tilde{s} \) and \( \tilde{r} \) are independent of each other, we have \( H((y, \tilde{s})|\tilde{r}) = H(y, \tilde{s}) \), and \( y \) can be derived from \( x \) so that \( H(y|x) = 0 \). We get

\[
Q_1 \leq I(x, y) - I(h, y) \tag{17}
\]

Due to \( Q_2 \leq 0 \), we can prove that

\[
\varepsilon \leq \alpha \beta (I(x, y) - I(h, y) - I(h, z)) \tag{18}
\]

For the multi-attribute case, \( \varepsilon \leq \alpha \beta (I(x, y) - I(h, y) - \sum I(h, z_i)) \). \( \square \)

### 6 Evaluation

To evaluate the effectiveness of our method in the Vertical Machine Learning scenario, we design some general evaluation metrics with several scenarios.

#### 6.1 Experiments Setting

The evaluation scenario is based on a unlearning task that trains on a deep neural network, where one or more sensitive features need to be deleted or not use as required by customs. However, the model performance for the main task should be preserved.

We experiment our method with three commonly used datasets, Fairface [Kärkkäinen and Joo, 2019], CelebA [Liu et al., 2018], Cifar10 [Krizhevsky and Hinton, 2010], and nowadays most prevailing representative architecture, ResNet models, e.g., ResNet-18, ResNet-34, ResNet-50, to unlearn from.

#### 6.2 Performance Metrics

Unlike other mature development domains in Machine Learning, evaluation criteria in Machine Unlearning has not been widely decided or recognized. Thus, we set up a series of evaluation metrics to assess the contribution of our method to Vertical Machine Unlearning with three key aspects.

**Unlearning Efficacy** In order to evaluate the effectiveness of the unlearning process, we consider an attack setting with parities of two, a model provider \( f(\theta_{m}; \cdot) \) and a malicious attacker. The attacker leverage a decoder \( f(\theta_{a}; \cdot) \) with pretrained RestNet18 as its backbone in attempting to infer the sensitive unlearnt feature denoted by \( z^* \) from the intermediate output of model \( h = f(\theta_{a}; x) \). So we focus on the prevention of sensitive attribute leakage and use the prediction accuracy of sensitive attribute as the indicator for the efficacy of Vertical Machine Unlearning. The lower the value, the better the unlearning works. We also visualize the efficacy by recovering the raw image from the intermediate output of model \( h = f(\theta_{a}; x) \), as shown in Fig. 3.

**Utility Retained** In spite of obtaining high unlearning efficacy, we also need to retain the performance of the main task of the trained model as much as possible, which we called Utility Retained. We use top-1 validation task accuracy as our measurement for this factor. For example, in Fairface dataset, top-1 accuracy for prediction of gender signify the utility capability of this dataset. Higher accuracy means better utility retained for this unlearning process.

**Unlearning Efficiency** The efficiency of unlearning serves as a novel indicator which aims at introducing as less additional overhead as possible when performing the unlearning process. Here we use training time and inference latency as the metrics for efficiency. Furthermore, we also measure the parameters and FLOPS to evaluate the model complexity and overhead.

| Datasets   | Models   | Baseline Efficiency | Efficacy (↓ better) | Utility (↑ better) | Baseline Utility |
|------------|----------|---------------------|--------------------|-------------------|-----------------|
| Fairface   | ResNet18 | 0.1421              | 0.130              | 0.8096            | 0.847           |
|            | ResNet34 | **0.1325**          | 0.135              | 0.798             | 0.835           |
|            | ResNet50 | 0.1367              | **0.1297**         | 0.8077            | 0.864           |
| CelebA     | ResNet18 | **0.4989**          | 0.5142             | 0.783             | 0.790           |
|            | ResNet34 | 0.5077              | **0.5035**         | 0.793             | 0.803           |
|            | ResNet50 | **0.4976**          | 0.4913             | 0.810             | 0.812           |
| Cifar10    | ResNet18 | 0.0103              | 0.0996             | 0.935             | 0.940           |
|            | ResNet34 | **0.101**           | 0.1057             | 0.936             | 0.942           |
|            | ResNet50 | 0.0993              | **0.098**          | 0.945             | 0.947           |

Table 1: Unlearning Efficacy versus Utility Retained: The middle two columns represent unlearning with our methods, and the first and fourth columns represent optimal baseline indicator for efficacy and utility. We can see that our methods reach both optimal results.

#### 6.3 Unlearning Performance: Unlearning Efficacy

To prove the effectiveness of unlearning efficacy, we are encouraged to create an optimal lower bound as the baseline indicator of our method. Apparently, deleting sensitive features directly from the image data samples is the most straightforward and valid way of eliminating certain features from the
model. Though with weak utility performance by removing other useful features classifying to the final task simultaneously, optimal unlearning efficacy obtained. So we choose it as the baseline value of our unlearning efficacy indicator, the closer to the value, the better our method achieves. Since the features are mixed together in the image data samples, we use GradCam [Selvaraju et al., 2017] to locate the attention area and spoil the feature. Fig. 3 represents the attention of gender area in fairface datasets. We can see from Tab. 1 that our method can reach optimal unlearning efficacy which close to the optimal baseline results in the third and forth columns. The sensitive attributes we choose here for fairface is ‘race’, and prediction attribute is ‘gender’. ‘Mustache’, ‘gender’ for celeba and ‘class’, ‘animated’ for cifar10.

6.4 Unlearning Performance: Utility Retained

Given the intrinsic challenge lies in Vertical Machine Unlearning, not only should we eliminating sensitive features, we also need to preserve the task-related information as much as possible. Obviously, the optimal situation to be obtained is with lower efficacy value and higher utility value. So to further evaluate the utility retained of our methods, We choose the original learnt model as our upper bound baseline for our utility measurement. The closer our prediction of task near to the baseline utility, the better of our methods performance. We can see from Tab. 1 that our method can reach optimal utility with effective unlearning efficacy.

6.5 Unlearning Efficiency and Model Complexity

Other than presenting superior performance on efficacy and utility retained after unlearning, our method also expect to achieve good performance with high efficiency. To evaluate the training and inference efficiency, we conduct experiments on Fairface dataset with 180 training epoch. we also measure the parameters size and FLOPs with our methods on ResNet50. As shown in Tab. 2, we can see that unlearning procedure do not introduce much overhead regarding the training and inference latency as well as model complexity, which can be a baseline level for further Vertical Machine Unlearning studies.

Table 2: Unlearning efficiency and model complexity: Training and inference latency of the unlearning process show more efficient compared to corresponding learning process, without introducing much overhead.

|                | Training Latency(epochs) | Inference Latency(epochs) | Parameters Size(M) | Flops(G) |
|----------------|--------------------------|---------------------------|--------------------|----------|
| Efficiency     |                          |                           |                    |          |
| Learning       | 50.67                    | 0.423                     | 23.512             | 0.6774   |
| Unlearning     | 44.99                    | 0.416                     | 23.574             | 0.8375   |

Table 3: Sensitive Feature Ablation: We select different sensitive features in order to eliminate the bias for certain features. We can see that they all reach similar high utility with sensitive features unlearned.

| Predicted Attributes | Sensitive Attributes | Efficacy (↓ better) | Utility (↑ better) |
|----------------------|----------------------|--------------------|-------------------|
| Gender               | Race                 | 0.130              | 0.8096            |
|                      | Age                  | 0.172              | 0.808             |
| Male                 | Mustache             | 0.5142             | 0.783             |
|                      | Smiling              | 0.4677             | 0.789             |

6.6 Ablation Study

Unlearning with different attributes selected To eliminate the influence of different attributes selected during unlearning process we also conduct additional experiments. For the Fairface dataset, we select both age and race as sensitive attributes with the main task of predicting gender, as shown in Tab. 3. We also visualize the effect of our methods by reconstructing images given the intermediate model output after unlearning. We show the results of raw images, attention with gradcam of raw images, reconstruction after unlearning from Fig. 3. The ambiguity in certain area of the reconstructed images after unlearning makes it impossible to infer certain feature, i.e., age in this scenario, which is in accordance with the purpose and quantitative results of our methods.

7 Conclusion

In this paper, we have proposed a novel insight of machine unlearning mechanism by selectively removing sensitive attributes from latent feature space, which can be regarded as a novel interpretation for emergent privacy protection legislation, namely, the vertical machine unlearning, a new research initiative for machine unlearning. We have defined the concept and elaborated the purpose of vertical machine unlearning to protect sensitive feature information from trained models. A representation detachment method have been proposed to progressively separate sensitive features from intermediate features which are used for final classification, via a deliberately designing the representation detachment loss. Moreover, to address the difficulties in calculating above loss, we have introduced an approximation method for the loss value with rigorous theoretical analysis. Our method have shown a new direction of protecting personal information and made an important step forward to the research and development of machine unlearning mechanisms.
References

[Batina et al., 2011] Lejla Batina, Benedikt Gierlichs, Emmanuel Prouff, Matthieu Rivain, Françoise-Xavier Staandaert, and Nicolas Veyrat-Charvillon. Mutual information analysis: a comprehensive study. Journal of Cryptology, 24(2):269–291, 2011.

[Bourtoule et al., 2021] Lucas Bourtoule, Varun Chandrasekaran, Christopher A Choquette-Choo, Hengrui Jia, Adelin Travers, Baiwu Zhang, David Lie, and Nicolas Papernot. Machine unlearning. In Proceedings of IEEE Symposium on Security and Privacy (SP), 2021.

[Brophy and Lowd, 2021] Jonathan Brophy and Daniel Lowd. Machine unlearning for random forests. In International Conference on Machine Learning, pages 1092–1104. PMLR, 2021.

[Cao and Yang, 2015] Yinzhi Cao and Junfeng Yang. Towards making systems forget with machine unlearning. In 2015 IEEE Symposium on Security and Privacy, pages 463–480. IEEE, 2015.

[De Bruyn, 2014] Michelle De Bruyn. The protection of personal information (popi) act: impact on south africa. 2014.

[Garcia et al., 2020] Lara Rocha Garcia, Edson Aguilera-Fernandes, Rafael Augusto Moreno Gonçalves, and Marcos Ribeiro Pereira-Barretto. Lei Geral de Proteção de Dados (LGPD): Guia de implantação. Editora Blucher, 2020.

[Gierlichs et al., 2008] Benedikt Gierlichs, Lejla Batina, Pim Tuyls, and Bart Preneel. Mutual information analysis. In International Workshop on Hardware and Embedded Systems, pages 426–442. Springer, 2008.

[Ginart et al., 2019] A Ginart, M Guan, G Valiant, and J Zou. Making ai forget you: Data deletion in machine learning. Advances in neural information processing systems, 2019.

[Gupta et al., 2021] Varun Gupta, Christopher Jung, Seth Neel, Aaron Roth, Saeed Sharifi-Malvajerdi, and Chris Waites. Adaptive machine unlearning. arXiv preprint arXiv:2106.04378, 2021.

[Huang et al., 2021] Hanxun Huang, Xingjun Ma, Sarah Monazar Efandi, James Bailey, and Yisen Wang. Unlearnable examples: Making personal data unexploitable. arXiv preprint arXiv:2101.04898, 2021.

[Kärkkäinen and Joo, 2019] Kimmo Kärkkäinen and Jungseock Joo. Fairface: Face attribute dataset for balanced race, gender, and age. arXiv preprint arXiv:1908.04913, 2019.

[Krizhevsky and Hinton, 2010] Alex Krizhevsky and Geoff Hinton. Convolutional deep belief networks on cifar-10. Unpublished manuscript, 40(7):1–9, 2010.

[Legislation, 2018] California Legislation. The california consumer privacy act, 2018. Last accessed 16 September 2017.

[Li et al., 2021] Mingjie Li, Shaobo Wang, and Quanshi Zhang. Visualizing the emergence of intermediate visual patterns in dnns. Advances in Neural Information Processing Systems, 34, 2021.

[Liu et al., 2018] Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Large-scale celebfaces attributes (celeba) dataset. Retrieved August, 15(2018):11, 2018.

[Liu et al., 2021] Bo Liu, Ming Ding, Sina Shaham, Wenjie Rahayu, Farhad Farokhi, and Zhihui Lin. When machine learning meets privacy: A survey and outlook. ACM Computing Surveys (CSUR), 54(2):1–36, 2021.

[Mantelero, 2013] Alessandro Mantelero. The eu proposal for a general data protection regulation and the roots of the ‘right to be forgotten’. Computer Law & Security Review, 29(3):229–235, 2013.

[Mehmood et al., 2016] Abid Mehmood, Lynkaran Natsugnanathan, Yong Xiang, Guang Hua, and Song Guo. Protection of big data privacy. IEEE access, 4:1821–1834, 2016.

[Morales et al., 2020] Aythami Morales, Julian Fierrez, Ruben Vera-Rodriguez, and Ruben Tolosana. Sensitivenets: Learning agnostic representations with application to face images. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(6):2158–2164, 2020.

[Papernot et al., 2016] Nicolas Papernot, Patrick McDaniel, Arunesh Sinha, and Michael Wellman. Towards the science of privacy and security in machine learning. arXiv preprint arXiv:1611.03814, 2016.

[Ren et al., 2021] Jie Ren, Mingjie Li, Zexu Liu, and Quan- shi Zhang. Interpreting and disentangling feature components of various complexity from dnns. In International Conference on Machine Learning, pages 8971–8981. PMLR, 2021.

[Sekhari et al., 2021] Ayush Sekhari, Jayadev Acharya, Gautam Kamath, and Ananda Theertha Suresh. Remember what you want to forget: Algorithms for machine unlearning. arXiv preprint arXiv:2103.03279, 2021.

[Selvaraju et al., 2017] Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In Proceedings of the IEEE international conference on computer vision, pages 618–626, 2017.

[Vepakomma et al., 2018] Praneeth Vepakomma, Otkrist Gupta, Tristan Swedish, and Ramesh Raskar. Split learning for health: Distributed deep learning without sharing raw patient data. arXiv preprint arXiv:1812.00564, 2018.

[Wang et al., 2021] Yulin Wang, Zanlin Ni, Shiji Song, Le Yang, and Gao Huang. Revisiting locally supervised learning: an alternative to end-to-end training. In 9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021. OpenReview.net, 2021.

[Yang et al., 2019] Qiang Yang, Yang Liu, Tianjian Chen, and Yongxin Tong. Federated machine learning: Concept and applications. ACM Transactions on Intelligent Systems and Technology (TIST), 10(2):1–19, 2019.