Debiasing Backdoor Attack: A Benign Application of Backdoor Attack in Eliminating Data Bias

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Abstract
Backdoor attack is a new AI security risk that has emerged in recent years. Drawing on the previous research of adversarial attack, we argue that the backdoor attack has the potential to tap into the model learning process and improve model performance. Based on Clean Accuracy Drop (CAD) in backdoor attack, we found that CAD came out of the effect of pseudo-deletion of data. We provided a preliminary explanation of this phenomenon from the perspective of model classification boundaries and observed that this pseudo-deletion had advantages over direct deletion in the data debiasing problem. Based on the above findings, we proposed Debiasing Backdoor Attack (DBA). It achieves SOTA in the debiasing task and has a broader application scenario than undersampling.

1 Introduction
Backdoor attack [Li et al., 2020] and adversarial attack are both traditional security risks in artificial intelligence. While adversarial attack is a technique to make a model produce wrong output results by adding a small human-designed perturbation, backdoor attack can make a model produce specified wrong output results by adding an artificially designed trigger. Since the backdoor attack was proposed, scholars mainly focused on the attack and defense algorithms of the backdoor attack. Major attack algorithms include BadNet [Gu et al., 2017] based on trigger training and TrojanNet [Liu et al., 2018b] based on model implantation. Later, other algorithms were proposed to enhance the stealthiness of backdoor attack [Liu et al., 2020]. Nowadays, a large number of defense and detection algorithms are proposed according to the weaknesses of backdoor attack [Gao et al., 2019; Liu et al., 2018a; Chen et al., 2019b].

The development of backdoor attack is similar to that of adversarial attack. In view of the research on the adversarial attack, we believe that the backdoor attack is worth exploring for model understanding. For example, in the study of adversarial training, those trained models not only have significant defensive effects against adversarial attack, but also significantly improve the interpretability of models [Goodfellow et al., 2015; Zhang and Zhu, 2019]. In addition, it has been shown that adversarial attack can be used in benign applications, such as face privacy protection [Zhao et al., 2021; Zhang et al., 2020], resisting malicious algorithms [Zhang et al., 2021] and adversarial data augmentation [Zhang and Sang, 2020]. It has been shown that backdoor attack can also be applied in benign scenarios. However, it has only been used in the field of security such as model protection [Adi et al., 2018; Jia et al., 2021] based on the designability of the trigger.

We would like to explore the properties present in backdoor attack and apply them to benign scenarios. Current measures of the effectiveness of trigger-based backdoor attack include ASR (Attack Success Rate), CAD (Clean Accuracy Drop), and stealthiness. We found that CAD was caused by pseudo-deletion by adding the trigger in backdoor attack, so as to make the model less generalizable. We managed to make a preliminary explanation of the CAD phenomenon by model classification boundaries. We proposed a new benign application based on backdoor attack by existing properties. Main contributions in this paper are shown as follows.

• We found that the attacked model produces a pseudo-deletion effect on samples with triggers, and provided a preliminary explanation with classification boundaries.
• We found that such pseudo-deleted samples can affect the model classification boundaries and make better use of the training data than direct deletion when applying to undersampling scenarios.
• We proposed Debiasing Backdoor Attack, which has achieved SOTA in task of debiasing on CelebA and UTK Face. We also validated its extension to multi-class classification and the avoiding of security risks.

2 Data Analysis
CAD plays an important role in the design and evaluation of backdoor attack. CAD refers to the difference in accuracy between the attacked model and the normal model on clean inputs. Since the main difference between the backdoor-attacked model and the normal model only exists in training samples labeled with triggers, we decided to start from those samples and examine how the deleting or editing of those samples affect model on the training process and final results.
2.1 Similarities and Differences between Backdoor Attack and Data Deletion on CAD

Deleting data from the training set decreases the generalizability of the model, which also causes the accuracy drop. We want to compare the difference between the accuracy drop caused by data deletion and adding triggers.

Taking two tasks of classifying numbers in MNIST dataset and classifying gender in CelebA dataset as examples, we randomly deleted $p\%$ of data from a class or added $p\%$ of triggers to the class, and compared the accuracy of test set, as shown in Fig. 1. It can be seen from Fig. 1 that accuracy between the attacked model and the model with data deletion is close. Therefore, we speculated that adding a trigger brings a similar effect with data deletion. Nonetheless, at higher $p\%$, the accuracy degradation caused by the backdoor attack will be slightly lower than that of the data deletion. In particular, when 100% of the training data of the target class is deleted, the accuracy of the trained model is 0% for that class when tested. However, when adding triggers to 100% of the data in that class, the model’s accuracy is still about 5% for that class.

Then we discussed how the similar effect occurred while adding a trigger in training process. By measuring the loss of samples with a trigger and normal samples separately, we verified whether there was a difference between samples with a trigger and normal samples of their contribution throughout the training process.

Afterwards, in both tasks we added 10% of the trigger to the class and recorded the training loss of samples with trigger and the normal samples, as shown in Fig. 2. As can be seen from Fig. 2, the sample loss with a trigger quickly drops orders of magnitude, which is different from that of the normal training samples. Therefore, at a certain stage of training, samples with the trigger make minor contribution to the overall gradient of the model, which is similar to the effect of deletion.

2.2 Preliminary Explanation of CAD in Backdoor Attack using Classification Boundaries

A study showed that samples with triggers and normal samples have a large distance in the feature space and can be easily divided into two clusters by a clustering algorithm [Chen et al., 2019a]. Based on the experiments in Sec. 2.1, above study can explain why adding triggers has the same effect as deleting them, but it doesn’t explain why there are differences at higher $p\%$. Therefore, we assume that these attacked samples can still have a certain impact on the classification boundaries in the normal sample cluster in the feature space.

If features of the backdoor trigger can be easily expressed under this assumption, the model will easily determine the class labeled with the trigger, so that the backdoor attack retains a high Attack Success Rate (ASR). Meanwhile, adding triggers to images means moving image samples from cluster of normal samples to cluster with triggers in feature space. This effect is equivalent to deleting those samples from normal samples, and we call the deletion effect brought about by backdoor attack as pseudo-deletion.

Although the samples with triggers are far from the cluster of the normal samples in the feature space, they still satisfy the classification boundary of the classification task in the feature space. These samples will also affect model’s classification boundaries in the normal samples cluster. Therefore the experiments in Sec. 2.1 produced generalization differences at higher $p\%$. We define the area of the normal samples in the feature space as the original space, and the direction of moving from the original space to the space with trigger samples as the trigger dimension. Fig. 3 shows the original space and the trigger dimension.

To verify the above assumption, we designed a toy dataset to describe the original feature space. We divided the square region into four blocks with 1,000 red and 1,000 blue points on the left and right, and set the bias rate as the ratio of points within the upper left and lower right corners. Points in each region are generated from a uniform distribution with a small perturbation of the normal distribution. Subsequently, we trained a small neural network based on the toy dataset. We selected 10,000 points of meshgrid in the sample space to plot the classification boundaries, and counted the misclassification of those points.

It can be seen from Fig. 4 that the model trained on all data causes a significant distortion of the classification boundary. Then, we used the undersampling method to delete points un-
Figure 3: Schematic diagram of the effect of deletion and pseudo-deletion on classification boundaries.

Figure 4: Visualization of classification boundaries under normal training, undersampling, and pseudo-deletion methods when bias rate is 0.8.

Figure 5: The value of Classification Boundary Error for normal training, undersampling, and pseudo-deletion methods with different bias rates. x-axis is the different bias rates, and y-axis is the value of Classification Boundary Error.

Figure 6: Visualizing the classification bounds for models trained using all true deletion, all pseudo-deletion, and a mixture of true deletion and pseudo-deletion methods. From left to right: all true deletion, all pseudo-deletion, red points pseudo-deletion blue points true deletion, red points pseudo-deletion blue points true deletion.

| Method | Classification Boundary Error | left | right | total |
|--------|-------------------------------|------|-------|-------|
| (a)    |                               | 52   | 52    | 104   |
| (b)    |                               | 53   | 25    | 78    |
| (c)    |                               | 0    | 171   | 171   |
| (d)    |                               | 159  | 7     | 166   |

2.3 Debiasing Effect of Backdoor Attack Under Extreme Conditions

From previous results, we can see that the pseudo-deletion based on the backdoor attack is significantly helpful in improving classification boundaries. Because adding trigger has the effect of deletion, it is natural to think that backdoor attack can be combined with undersampling methods. Thus, our next goal is to test whether it can be applied to model debiasing.

Undersampling method is an effective and simple method in the field of debiasing. Instead of deletion in undersampling, pseudo-deletion is considered to test whether the algorithm can benefit from it. Our target was to start experiment on CelebA dataset. Two variables with the strongest Pearson coefficients with gender, Wearing_Lipstick (Pearson=-0.8196) and Heavy_Makeup (Pearson=-0.6502), were chosen as the classification targets with gender bias.

The evaluation is based on Equal Opportunity (Opp.), Equalized Odds (Odds) and Equalized Accuracy (EAcc.), which are commonly used in the field of debiasing. The above concepts can be expressed by True Positive Rate (TPR) and True Negative Rate (TNR) as follows:

\[
\text{Opp.} = \left| \frac{TPR_{A=0} - TPR_{A=1}}{TNR_{A=0} + TNR_{A=1}} \right|
\]

\[
\text{Odds} = \frac{1}{2} \left[ \left| TPR_{A=0} - TPR_{A=1} \right| + \left| TNR_{A=0} - TNR_{A=1} \right| \right]
\]

\[
\text{EAcc.} = \frac{1}{4} \left[ TPR_{A=0} + TNR_{A=0} + TPR_{A=1} + TNR_{A=1} \right]
\]
Table 1: The debiasing effect on Wearing Lipstick when Male was set as the bias variable.

| Method         | Target | Bias | Opp. ↓ | Odds ↓ | EAcc ↑ | Acc. ↑ |
|----------------|--------|------|--------|--------|--------|--------|
| Undersampling  | T=1    | M=1  | 51.06  | 32.67  | 78.46  | 32.11  |
|                | T=0    | M=0  | 88.10  | 74.87  |        |        |
| Pseudo-deletion| T=1    | M=1  | 53.19  | 25.62  | 79.14  | 86.72  |
|                | T=0    | M=0  | 97.55  | 86.99  |        |        |

Table 2: The debiasing effect on Heavy Makeup when Male was set as the bias variable.

| Method         | Target | Bias | Opp. ↓ | Odds ↓ | EAcc ↑ | Acc. ↑ |
|----------------|--------|------|--------|--------|--------|--------|
| Undersampling  | T=1    | M=1  | 40.91  | 45.47  |        |        |
|                | T=0    | M=0  | 99.25  | 89.93  |        |        |
| Pseudo-deletion| T=1    | M=1  | 22.73  | 32.41  |        |        |
|                | T=0    | M=0  | 59.38  | 89.77  |        |        |

As shown in Table 1 and Table 2, the pseudo-deletion method has great potential in debiasing. Compared with undersampling, the existing of those pseudo-deleted samples in the feature space will make the model to have better performance. In addition, pseudo-deletion can keep samples balanced in the dataset same as undersampling, and makes the boundary fair and smooth so as to achieve debiasing.

### 3 Method

The undersampling method is often used for data-debiasing by deleting large quantities of unbalanced data, sometimes leading to non-convergence. By applying pseudo-deletion to undersampling, we proposed Debiasing Backdoor Attack (DBA) method so as to solve the problem in binary classification with single bias variable, and branched out into simultaneously classifying multiple binary classification. Besides, a framework was brought out in order to describe our method while considering to use backdoor attack safely.

#### 3.1 Debiasing Backdoor Attack for Binary Classification Task

For binary classification, we replaced data deleting with pseudo-deletion in the undersampling method. The process can be divided into three steps. First, the data distribution in training set was counted, based on which the proportion of pseudo-deletion triggers added to each sample was calculated as follows:

$$R(A = i, Y = j) = \frac{N_{\text{trigger}}(A = i, Y = j)}{N(A = i, Y = j)}$$

$$= \max\{N(A = i, Y = j) - N(A = i, Y = \bar{j}), 0\}$$

where $A$ refers to the bias attribute, $Y$ refers to the target attribute, $R(\cdot)$ refers to the proportion of the trigger added in that case, $N(\cdot)$ refers to the number of training samples that meet the case, and similarly $N_{\text{trigger}}(\cdot)$ refers to the number of samples that need to be added to the trigger under that case. Second, add different triggers to samples of different bias variables according to the calculated proportions, thus generating a new training set $D_{\text{trigger}}$. Third, the model was trained on the newly generated dataset $D_{\text{trigger}}$ to obtain a fair model.

#### 3.2 For Multi-class Classifications Task

In this section, we expanded Debiasing Backdoor Attack to multi-classification tasks with a single bias variable. Multiple binary classification tasks can be viewed as $N$ single classification tasks. For each single classification task, we designed two dedicated triggers, thus there will be $2N$ kinds of triggers in $D_{\text{trigger}}$. Unlike deleting data, pseudo-deletion triggers can be added in the image at the same time as much as needed to form trigger barcodes. Therefore, the pseudo-deletion method can be used to debias multiple binary classification problems, as is shown in Fig. 7.

The original undersampling for multiple binary classification has to take the intersection of each class to make every class distribution balanced, and delete the rest of large amount of data. Under that condition, few data will be last to satisfy the model training. In contrast to undersampling methods, Debiasing Backdoor Attack can balance distribution easily when applied in the multiple binary classification task.

#### 3.3 Avoiding Security Risks

In order to avoid security risks of backdoor attack, we proposed Implicit Backdoor Attack for training and two solu-
tions for testing, namely, Internal Padding and Equivalent Pruning.

**Implicit Backdoor Attack**: Change RGB channels of the image to RGBT channels, by adding a new channel T, which is zero by default. The channel T is specifically used to adding triggers and other channels stay unchanged.

**Internal Padding**: During the test, users are only allowed to pass in RGB three-channel images. The algorithm has to add a T channel on images internally with all zeros in order to feed into models, through which users cannot edit the T channel so as to keep models safe.

**Equivalent Pruning**: Parameters of the first layer are edited using the pruning algorithm to remove parameters for the T layer so that the model only supports RGB input, thus avoiding security risks.

## 4 Experiments

### 4.1 Experiments Setting

#### Dataset

**CelebA**: CelebA dataset [Liu et al., 2015] has 200k face images and is annotated with 40 attributes. Male $^1$ and Young attributes were set as bias variables and the rest as target attributes. The training set split method in tensorflow-dataset was applied.

**UTK Face**: UTK Face dataset [Zhang et al., 2017] has 23,705 face images and is labeled with 3 attributes (age, gender, and race). We set the ratio of training set to test set as 7:3, and chose Race (whether or not white race) as the bias attribute to predict whether people were older than 35.

#### Detail Setting

For all algorithms we set ResNet9 as the backbone network, selected Adam as the optimizer, and set the learning rate to 0.001. For multiple binary classification prediction tasks, we set ResNet9 to have multiple linear output heads, with each head used to predict one attribute. We chose Opp., Odds, EAcc., and Acc. to evaluate algorithms, and do not record the value of Opp. and Odds if the algorithm does not converge.

#### Comparing Models

Typical debiasing alternatives are supplied for comparison:

- **Undersampling** [Zhou and Liu, 2006]: discarding samples with majority bias variable to construct a balanced dataset.
- **Reweighting** [Kamiran and Calders, 2011]: assigning different weights to samples and modifying the training objectives to softly balance the data distribution.
- **Adversarial Learning** [Ganin and Lempitsky, 2015; Wadsworth et al., 2018]: the typical in-processing debiasing solution by adversarially learning between the target and bias tasks.
- **Fairness GAN** [Sattigeri et al., 2019]: an auxiliary classifier GAN that strives for equality of opportunity.

$^1$Since the attributes 5_Clock_Shadow, Goatee, Mustache, No_Beard, and Sideburns are not suitable for studying gender bias, we do not discuss these attributes in our subsequent experiments.

### 4.2 Debiasing Effect

First, we conducted experiments on the classification of single attributes and reproduced four commonly used algorithms, namely, Normal, Undersampling, Reweighting and Adversarial Learning. In Table 3, Male was set as the bias variable. Opp., Odds, EAcc. and Acc. are the average of remaining 34 groups attributes in CelebA. It shows that our proposed method has a huge debiasing advantage over the above mentioned four methods. Although a decline in the accuracy, Opp., Odds, EAcc. are significantly improved. In Table 4, Young was set as another bias variable for the remaining 39 attributes. It shows that the score of our algorithm on Opp. is half lower than that of Undersampling on age bias. To avoid the error caused by the dataset, Race

| Method        | Opp↓  | Odds↓ | EAcc↑ | Acc↑  |
|---------------|-------|-------|-------|-------|
| Normal        | 21.28 | 15.21 | 74.99 | 87.17 |
| Undersampling | 6.96  | 6.99  | 79.86 | 79.22 |
| Reweighting   | 10.00 | 7.81  | 75.47 | 78.83 |
| Adversarial Learning | 17.38 | 14.02 | 71.82 | 85.98 |
| DBA(Ours)     | 4.73  | 5.58  | 81.21 | 82.13 |

Table 3: The average effect of different algorithms for debiasing the remaining 34 attributes in CelebA dataset with Male as the bias variable.

| Method        | Opp↓  | Odds↓ | EAcc↑ | Acc↑  |
|---------------|-------|-------|-------|-------|
| Normal        | 7.27  | 6.05  | 80.22 | 89.77 |
| Undersampling | 5.54  | 5.09  | 82.95 | 83.67 |
| Reweighting   | 5.13  | 5.01  | 78.10 | 81.67 |
| Adversarial Learning | 6.45  | 5.62  | 79.01 | 88.12 |
| DBA(Ours)     | 1.63  | 4.30  | 83.99 | 82.12 |

Table 4: The average effect of different algorithms for debiasing the remaining 39 attributes in CelebA dataset with Young as the bias variable.

- FFVAE [Creager et al., 2019]: learning compact representations that are useful for reconstruction and fair prediction.
- TAC [Hwang et al., 2020]: the method attempts to train the fairness-aware image classification model without protected attribute annotations.
- MFD [Jung et al., 2021]: a systematic approach which reduces algorithmic biases via feature distillation for visual recognition tasks.
- FD-VAE [Park et al., 2021]: a VAE algorithm that learns fair representations by decomposing the data representation into three independent subspaces.
- Fair Mixup [Chuang and Mroueh, 2021]: a data augmentation strategy for imposing the fairness constraint.
- BiFair [Øzdayi et al., 2021]: a training algorithm that can jointly minimize for a utility and a fairness loss.
- RNF-GT [Du et al., 2021]: discouraging the classification head from capturing spurious correlation between fairness sensitive information in encoder representations with specific class labels.
was set as the bias variable on UTK Face to predict whether the age was older than 35. As shown in Table 5, under the extreme bias of Race, our algorithm still has good results while the Reweighting algorithm appears to be non-convergent.

The frequencies of non-convergence of each algorithm in the 74 sets of experiments are shown in Table 6. In extreme cases, the Reweighting algorithm is most prone to non-convergence due to loss imbalance. The Undersampling algorithm will also fail to converge due to the deletion of excess data. The Adversarial Learning will not converge for its complex training process. Compared with those methods, our method has strong applicability under different conditions.

Second, we looked for eight new debiasing methods with the same experimental settings as ours and extracted their best results for a fair comparison. As shown in Table 7, our method has so far achieved SOTA in debiasing.

Specially, our algorithm can be applied in debiasing multiple attributes simultaneously. In Table 8, our algorithm for classifying multiple attributes performs better than average results of Adversarial Learning and Reweighting in classifying a single attribute.

4.3 Ablation Experiments
Ablation experiments aim to test whether different patch sizes and colors will successfully achieve pseudo-deletion. Results are shown in Table 9.

Unlike backdoor attack methods that consider invisibility, the color and size of the trigger will not affect the results of the backdoor attack when a simple style of trigger is used.

4.4 Results of Avoiding Security Risks
Results of EAcc., parameter numbers and resources costing among normal Debiasing Backdoor Attack, Internal Padding and Equivalence Pruning are shown in Table 10.

As for as EAcc., there is no difference between the three methods, whereas the normal method has security risks.

5 Conclusions
In summary, starting from the observation on CAD, we found that the backdoor attack, as a substitute for data deletion methods, had the potential to eliminate data bias. On top of that, we believe other phenomena in backdoor attack are worth discussion, for instance, by studying the learning speed of trigger, we may obtain some properties such as the learning order of model features. As a way of model probe to understanding model properties, backdoor attack is of considerable value to exploring the mechanism of deep learning and offering alternative solutions to notorious problems.

### Table 5: The effect of debiasing different algorithms on whether the age is older than 35 in UTK Face dataset with Race as the bias variable.

| Method          | Target | Bias     | Opp↓ | Odds↑ | EAcc↑ | Acc↑ |
|-----------------|--------|----------|------|-------|-------|------|
| Normal          | T=1    | 74.17    | 17.01| 11.54 | 77.44 | 81.60|
|                 | T=0    | 86.18    | 92.25|       |       |      |
| Undersampling   | T=1    | 74.82    | 6.47 | 4.31  | 76.00 | 77.60|
|                 | T=0    | 79.35    | 81.50|       |       |      |
| Reweighting     | T=1    | 0.000    | 5.00 | 0.00  | 50.00 | 63.62|
|                 | T=0    | 100.00   | 100.00|      |       |      |
| Adversarial     | T=1    | 93.71    | 11.80| 10.92 | 79.51 | 78.47|
| Learning        | T=0    | 66.19    | 76.23|       |       |      |
| DBA(Ours)       | T=1    | 83.07    | 4.71 | 3.50  | 80.32 | 80.07|
|                 | T=0    | 81.07    | 78.78|       |       |      |

### Table 6: Counts of non-convergence cases for different algorithms in the above 74 sets of experiments.

| Method          | Num  |
|-----------------|------|
| Normal          | 0    |
| Undersampling   | 2    |
| Reweighting     | 12   |
| Adversarial     | 3    |
| DBA(Ours)       | 0    |

### Table 7: Comparison results between our method and 8 methods in the same experimental configuration.

| Method          | Bias-Target | Opp↓ | Odds↑ | EAcc↑ | Acc↑ |
|-----------------|-------------|------|-------|-------|------|
| Normal(Male)    | 22.54       | 15.38| 70.44 |       | 86.74|
| DBA(Male)       | 12.73       | 10.85| 75.43 |       | 82.97|
| Normal(Young)   | 6.64        | 5.11 | 74.08 |       | 88.77|
| DBA(Young)      | 4.83        | 6.14 | 80.44 |       | 84.44|

### Table 8: The average effect of a special debiased scene for classifying multiple attributes at the same time.

| Experiments Setting | Results          |
|---------------------|------------------|
| Red Patch, 25pix*25pix | Success        |
| Blue Patch, 25pix*25pix | Success       |
| Red Patch, 10pix*10pix | Success       |
| Red Patch, 5pix*5pix    | Success        |

### Table 9: Results of whether patch works with different experimental settings.

| Method          | EAcc↑ | Params | Cost   |
|-----------------|-------|--------|--------|
| Normal          | 81.21 | 4.908M | 1.472 GFlops |
| Implicit + Internal Padding | 81.21 | 4.911M | 1.533 GFlops |
| Implicit + Equivalence Pruning | 81.21 | 4.908M | 1.472 GFlops |

### Table 10: Comparison of different methods for avoiding security risks in terms of EAcc., number of parameters, and computational resource usage.

Compared with the other two safe methods, the Equivalence Pruning perform better which is suitable for model deployments. However, it is difficult to handle. Meanwhile, Internal Padding fits for testing in experimental environments.
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