Repairing Group-Level Errors for DNNs Using Weighted Regularization

ZIYUAN ZHONG* and YUCHI TIAN*, Columbia University, USA
CONOR J.SWEENEY, Columbia University, USA
VICENTE ORDONEZ, Rice University, USA
BAISHAKHI RAY, Columbia University, USA

Deep Neural Networks (DNNs) have been widely used in software making decisions impacting people’s lives. However, they have been found to exhibit severe erroneous behaviors that may lead to unfortunate outcomes. Previous work shows that such misbehaviors often occur due to class property violations rather than errors on a single image. Although methods for detecting such errors have been proposed, fixing them has not been studied so far. Here, we propose a generic method called Weighted Regularization (WR) consisting of five concrete methods targeting the error-producing classes to fix the DNNs. In particular, it can repair confusion error and bias error of DNN models for both single-label and multi-label image classifications. A confusion error happens when a given DNN model tends to confuse between two classes. Each method in WR assigns more weights at a stage of DNN retraining or inference to mitigate the confusion between target pair. A bias error can be fixed similarly. We evaluate and compare the proposed methods along with baselines on six widely-used datasets and architecture combinations. The results suggest that WR methods have different trade-offs but under each setting at least one WR method can greatly reduce confusion/bias errors at a very limited cost of the overall performance.

Additional Key Words and Phrases: deep neural network, software repair, robustness, fairness

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1 INTRODUCTION

Deep Neural Networks are widely used nowadays as components in many critical applications like self-driving cars, face-recognition, medical diagnosis, etc. "Although DNN models do not contain any code logic like more traditional forms of software engineering, these models can still suffer from a different form of "serious bugs"[28, 68]. For example, it has been found that Google photo-tagging app tagged pictures of two dark-skinned people as "gorillas" [21]. Analogous to traditional software bugs, previous work in Software Engineering (SE) has denoted classification errors like this as model bugs [45] that arise from either biased training data, problematic model architecture, training procedure error or the combination of them.

*Both authors contributed equally to this research.
DNN classification errors fall into three main categories, instance-wise, group-wise, and dataset-wise. Instance-wise error has been well studied in the previous literature. In essence, an instance-wise error happens when a DNN model misclassifies different semantic-preserving transformations of a given input [47, 57, 65, 86]. Over the years, researchers have found numerous such transformations such as norm-bounded perturbation [47], natural transformation [14], or physical attack [16] to fool a well-trained DNN classifier. The fixing strategies such as adversarial training, data augmentation are also widely studied [14, 19, 47]. Dataset-wise error is essentially the model’s overall accuracy being worse than expected. Previous work have shown promising fixing results using strategies like data augmentation [58], weight adaptation [83] and input selection using differential heat maps [45].

Different from the above two, group-wise error is about the DNN model’s weak performance on differentiating among certain classes or has inconsistent performance across classes [68]. There are very few work on repairing group-wise errors and it only receives attentions recently [68]. This type of bugs is very concerning since it has been found to relate to many real-world notorious errors. Some work have proposed techniques to detect this kind of errors, however, until now, no fixing methods have been proposed for repairing them. To bridge this gap, in this work, we propose a generic fixing method for repairing such errors of any given DNN models.

The group-wise errors definition proposed in [68] consists of two main types with different root causes: (i) **Confusion**: The model cannot differentiate one class from another. For example, Google Photos confuses skier and mountain [48]. (ii) **Bias**: The model shows disparate outcomes between two related groups. For example, Zhao et al. [84] find classification bias in favor of women on activities like shopping, cooking, washing, etc.. Figure 1 presents two concrete examples of both types of errors from COCO and Image-Net reported in [68]. Note that unlike an instance-wise error which affects a particular misclassified image or a dataset-wise error which affects all the misclassified images in the dataset, such group-wise error affects all the images falling into the groups.

The causes of a group-wise error can be that certain classes are harder to be differentiated from each other. For example, in CIFAR-10, dog and cat tend to confuse even a state-of-the-art DNN model. Figure 2 shows the confusion matrix for a well-trained VGG11-BN model on CIFAR-10. The (i,j)-th entry is the probability of the class i being predicted to class j by mistake. It can be seen that the model is much more likely to confuse between dog and cat with a confusion of 0.081 meaning given a uniformly randomly sampled dog or cat image there is a 8.1% chance for the model to make a mistake by predicting the image to belong to the other class. This is much larger than 0.025 which is the second largest pairwise confusion. One potential cause of the model’s high confusion between dog and cat is that these two classes share many common semantic features. As a result,
the two classes tend to be very close to each other in the representation space and the decision boundary between them might not be "fine-grained" enough for correct classification on some dog and cat images. We denote the error-inducing classes as target classes. To fix the errors of the target classes, the model needs to take more effort to learn from them. Note that this is similar to solving the problem of class imbalance\[7, 29\] in which case a given model is supposed to take more effort on some minority classes in order to achieve improved class-balanced error. The key differences are two-fold. First, group-wise errors are not necessarily caused by class imbalance. As shown in the example of CIFAR-10 in Figure 2, although each class in the training data has the same number of samples, the model still suffer from much higher confusion between dog and cat compared with other pairs. Second, the two share different optimization objectives. The objective in our setting is mitigating confusion/bias while maintaining overall accuracy rather than improving class-balanced accuracy. It is possible for a model to have similar class-wise accuracy for each class but still suffer from high pair-wise confusion between some pairs of classes.

For large and complex DNN models, complete training from scratch may not be possible. Sometimes no extra data can be collected, either. In these cases, fine-tuning with potential data augmentation can be applied to enforce the model to learn to better classify the target classes. When fine-tuning is not possible or training data cannot be accessed, (for example, the user does not have right to access the data) the output can be modified to fix the errors while sacrificing the overall performance to some extent.

![Confusion matrix of VGG11-BN on CIFAR-10.](image)

**Fig. 2.** Confusion matrix of VGG11-BN on CIFAR-10.

Based on these observations as well as inspiration from existing works on the problem of class imbalance, we propose a generic method called weighted regularization (WR). WR consists of multiple concrete methods including weighted augmentation (w-aug), weighted batch normalization (w-bn), weighted output smoothing (w-os), weighted loss (w-loss), and weighted distance-based regularization (w-dbr). These methods function at different stages of a given DNN’s training or

![Overview of Weighted Regularization for Target Fixing](image)

**Fig. 3.** Overview of Weighted Regularization for Target Fixing
inference time Figure 3. In particular, if retraining is allowed and training data are provided, w-aug assigns more weights to the target classes during the retraining, w-bn shifts the distribution of the activation values induced by the input at every batchnorm layer (assuming the model has batchnorm layers), and w-loss and w-dbr modify the loss function by assigning more weights to the erroneous instances and regularizing the class centroids in the representation space, respectively. Such fine-tuning strategies enable the model to emphasize more on the instances of the target classes and thus more likely to avoid the errors involving the target classes. If fine-tuning and training data are not provided, w-os multiplies the model’s prediction on target classes by a smaller user-specified constant. In other words, making the model predict less the target class. In this way, the group-wise errors on those unsure data points can be avoided.

We illustrate an ideal fixing result and potential fixing results after applying these methods in Figure 4 with an example consists of three classes (square, circle and diamond). The colors represent the model’s prediction while the dashed lines denote the model’s decision boundary. Figure 4(a) shows that the original model tends to confuse between square and circle since these two classes are very close to each other. Ideally, a fixing method wants to fine-tune the model such that the decision boundary becomes that in Figure 4(d). w-os tends to solve the confusion issue by contracting the decision boundary of the target classes as illustrated in Figure 4(c). w-aug, w-loss, and w-dbr try to reduce confusion by shifting the decision boundary. They may be able to achieve Figure 4(d) but may also sacrifice the decision boundary for other classes sometimes and get the decision boundary in Figure 4(b) instead. w-bn comes in between: on the one hand, it tends to contract the decision boundary as w-os; on the other hand, it tends to shift the decision boundary through fine-tuning.

To check what the effectiveness of the proposed methods and what are their fixing performance in practice, we evaluate them on fixing confusion error and bias error for both single-label and multi-label image classification in six different settings involving four datasets and five DNN architectures. Our experiments show that in every setting, a subset of our proposed methods can significantly reduce the error significantly and most of time at least one method can have similar accuracy (or mean average precision for multi-label image classification) and lower confusion/bias error than the original model at the same time. We also provide some analysis of the proposed methods’ performance and applicability. In summary, we make the following contributions:

- We propose a generic method for targeted group-wise error fixing of DNN models, WR, which consists of five specific methods.
- We compare the five proposed methods performance and show their effectiveness on fixing two types of group-wise errors.

Our code is available at https://github.com/yuchi1989/deeprepair.
2 BACKGROUND

2.1 Image Classification

This work focuses on two types of image classification problems. In a single-label classification problem, each datum is associated with a single label \( l \) from a set of disjoint labels \( L \) where \(|L| > 1\). Typical datasets include CIFAR-10/CIFAR-100 [33] where an image can be categorized into one of 10/100 classes. In a multi-label classification problem, each datum is associated with a set of labels \( Y \) where \( Y \subseteq L \). MS-COCO[38] is a commonly used dataset where an image can be labeled as car, person, traffic light and bicycle.

Given any single- or multi-label classification task, a DNN classifier software tries to learn decision boundaries that can separate the classes. In particular, all members of one class, say \( C_i \), should be categorized identically irrespective of their individual features, while all members of any other class, say \( C_j \), should not be categorized to \( C_i \) [5]. A DNN represents a given input image in an embedded space with the feature vector at a certain intermediate layer and uses the layers after as a classifier to classify these representations. The class separation between two classes estimates how well the DNN has learned to separate each class from the other. If the embedded distance between two classes is too small compared to other classes, or lower than some pre-defined threshold, the DNN is likely to not be able to separate them from each other.

2.2 Group-wise Error

The proposed method aims to address the two types of group-wise errors proposed in [68]. We provide the definitions of them in the following.

2.2.1 Confusion Error. A confusion error occurs when a DNN frequently makes mistakes in disambiguating members of two different classes.

Type1 confusions: In single-label classification, Type1 confusion occurs when an object of class \( A \) (e.g., dog) is misclassified to another class \( B \) (e.g., cat). We call class \( A \) and class \( B \) as target classes since they are the classes inducing the error. For all the objects of class \( A \) and \( B \), it can be quantified as:

\[
type1conf(A, B) = \text{mean}(P(A|B), P(B|A))
\]

In other words, it is the DNN’s probability to misclassify class \( B \) as \( A \) and vice-versa, and takes the average value between the two. For example, given two classes cat and dog, \( type1conf \) estimates the mean probability of dog misclassified to cat and vice versa. Note that, this is a bi-directional score, i.e. misclassification of \( B \) as \( A \) is the same as misclassification of \( A \) as \( B \).

Type2 confusions: In multi-label classification, Type2 confusion occurs when an input image contains an object of class \( A \) (e.g., person) and no object of class \( B \) (e.g., bus), but the model predicts both classes. For a pair of classes, this can be quantified as:

\[
type2conf(A, B) = \text{mean}(P((A, B)|A), P((B, A)|B))
\]

In other words, it is the probability to detect two objects in the presence of only one. For example, given two classes bus and person, \( type2conf \) estimates the mean probability of person being predicted while predicting bus and vice versa. This is also a bi-directional score.

2.2.2 Bias Error. A DNN model is biased if it associates two classes differently with a third class. For example, consider three classes: man, woman, and skis. An unbiased model should not have different error rates while classifying man or woman in the presence of skis. To measure such bias formally, confusion disparity (cd) is defined to measure differences in error rate between classes \( A \) and \( C \) and between \( B \) and \( C \):

\[
cd(A, B, C) = |\text{error}(A, C) - \text{error}(B, C)|,
\]
where the error measure can be either type1conf or type2conf as defined earlier. cd essentially estimates the disparity of the model’s error between classes $A, B$ (e.g., man, woman) w.r.t. a third class $C$ (e.g., skis).

Without loss of generality, we assume $error(A, C) \geq error(B, C)$. We call class $A$ positive target class, class $B$ negative target class, and class $C$ anchor target class. The three classes $A, B, C$ are also collectively called target classes.

### 2.2.3 Repairing Group-wise Error

We define if a group-wise confusion/bias error (type1conf, type2conf, or cd) of a given DNN model is repaired if that error is reduced more than a desired user-specified threshold $\lambda_1$ after repairing. Note that it is sometimes acceptable to sacrifice the model’s overall accuracy to some extent as long as the overall accuracy loss is smaller than a user-specified threshold $\lambda_2$. In this work, if not stated otherwise, we consider the error reduction to be 25% of the original error and accuracy loss to be 1% of the original accuracy. We next provide some usage scenarios.

Usage scenarios for repairing confusion errors: one usage scenario is fixing the erroneous model used in google photo which was once reported to tag black people to gorillas by mistakes [21]. This is likely caused by the model’s confusion between black people and gorillas. Given the model was trained using lots of resources, the developer might want to fix this confusion error through fine-tuning or other strategies rather than retrain a new model from scratch. Meanwhile, it might be tolerable for the model to make some less irritating confusions (e.g. confusion between two very similar genres of dogs) as a trade-off. Another usage scenario is when one wants to have the pair-wise confusions among multiple pairs roughly similar. This relates to group-level fairness definitions (e.g., equalized odds, equal opportunity, etc.) which seek for group-level treatment to be roughly similar [50].

Usage scenarios for repairing bias errors: one usage scenario is fixing the well-trained but biased multi-label classification models which have been shown to be much more likely to wrongly classify a woman to a man in the context of doing sports like surfing or skiing [68]. Such biased behaviors involving gender are undesirable and can also be regarded as a violation of a kind of group-level fairness property. In fair ML, it is sometimes considered acceptable to slightly sacrifice the overall accuracy to avoid certain fairness property’s violation. In fact, such trade-offs between group-level fairness and accuracy are unavoidable (except in extreme cases) and the methods trying to achieve the best trade-offs w.r.t. some group-level fairness properties have been studied in previous work [2, 24].

### 2.3 Regularization

Based on the no free lunch theorem [75], a specific machine learning algorithm needs to be designed in order to perform well on a specific task. One approach is to leverage regularization to give an algorithm a preference for one solution over another solution. As proposed by Goodfellow et al. [20], regularization are all different approaches expressing preference for different solutions. One well-known technique of regularization is by imposing a penalty into an optimization process to prevent models from overfitting. For example, the norm penalty of a DNN model’s weight can be added into the loss function to encourage smaller weight and to prevent overfitting. In this work, we apply the idea of regularization in the context of fixing group-wise errors. In the current work, the proposed five concrete weighted regularization methods, which are respectively applied in input phase, model layer phase, output phase and loss phase of training or inference, all try to fix a given target confusing pair or bias triplet by forcing the DNN models to take more effort for the target classes.
3 METHODOLOGY

Our goal is to reduce a DNN model’s confusion error on a targeted pair or bias error on a targeted triplet (defined in Section 2.2) while maintaining its overall accuracy. The targeted pair or triplet are user-specified e.g. the laptop, mouse pair and the surfing, man, woman triplet as shown in Figure 1b. To achieve our goal, an intuitive approach is to let the DNN model focus more on the targeted pair/triplet. All of our proposed methods follow this intuitive approach but differ in at which stage of the DNN retraining/inference they assign more weights to the targeted pair/triplet as shown in Figure 3. There are two reasons of designing five methods. First, there are underlying intuitions for each method and it is not clear which method will perform the best under each setting. Second, since these methods function at different stages, they have different applicable scenarios.

In the following subsections, we will first introduce the loss function of a generic DNN image classifier to provide notations and serve as a baseline. Next, we introduce each method by showing the underlying motivations and connections with existing literature, how they are developed to fix the confusion error and the bias error for both single-label classification and multi-label classification, and finally their applicable scenarios. For simplicity, we only explain our methods in fixing confusion error for one pair of classes and bias error for one triplet of classes. However, our method can be easily extended to fix multiple pairs or triplets by treating every target pair/triplet the same way as the one demonstrated and in Section 5. To demonstrate the method’s generalizability to multiple pairs, we show the effectiveness of applying our methods to fix confusion errors involving multiple pairs.

3.1 Baseline: Original Model (orig) and Fine-tuned Original Model (orig-ft)

The original DNN model is trained using a standard objective function:

$$\text{Loss}_{\text{orig}} = \mathbb{E}_{(x,y) \sim D} L(f(x), y)$$

where $D$ is the underlying data distribution of input $x$ and label $y$, and $L$ is a loss function. Two widely used classification loss functions are cross-entropy loss and L2 loss. We additionally consider a fine-tuned model which applies the same fine-tuning procedures as w-aug, w-bn, w-loss, and w-dbr discussed in the following but using $\text{Loss}_{\text{orig}}$ as the objective function during the fine-tuning process.

3.2 Regularize Input: Weighted Augmentation (w-aug)

The weighted augmentation method fine-tunes a given DNN model with reweighted sampling probability for images according to their classes. In particular, it samples more from the target classes and less from the non-target classes. With more sampled from the target classes, the DNN model is expected to be able to better identify these target classes. This method is similar to the over-sampling used to addressing class imbalance[7, 29]. The difference is that in our setting the augmented classes are the target classes while in the class imbalance setting the augmented classes are the minority classes. However, target classes are not necessarily the minority classes. For example, in CIFAR-10, although all the classes have the same number of samples, large confusion error exist for the dog and cat pair. The loss function for w-aug is defined as:

$$\text{Loss}_{\text{aug}} = \mathbb{E}_{(x,y) \sim D'} L(f(x), y)$$

where the probability density function for the weighted distribution $D'$ is

$$pdf'(X, Y) = \begin{cases} pdf(X, Y), & \text{if } y \in Y_{\text{target}} \\ \rho \times pdf(X, Y), & \text{otherwise} \end{cases}$$

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where $pdf$ is the probability density function of the original data distribution $D$. In essence, the images that have labels belonging to the target classes are oversampled by scaling the weights of the non-target classes by a user specified constant $\rho \in [0, 1]$ during fine-tuning. The smaller $\rho$ is, the less effort the DNN model will spend on the non-target classes compared with the target classes during the fine-tuning.

3.2.1 Fixing confusion error. The target classes are the confused pair of classes $A$ and $B$ so the DNN should be able to better distinguish one from the other.

3.2.2 Fixing bias error. The target classes are the biased triplet of classes $A$, $B$ and $C$ so the DNN should be able to better differentiate the three.

3.2.3 Applicable Scenario. Fine-tuning is allowed.

3.2.4 Extension to multiple pairs/triplets. We include all the involved classes in the pairs/triplets into $Y_{target}$.

3.3 Regularize Model: Weighted Batch Normalization (w-bn)

The weighted batch normalization method assumes the existence of batch norm layers of a given DNN model. Batch normalization is usually applied after convolutional layers for more stable training and faster convergence[27] by making the loss landscape smoother[61]. It re-centers and re-scales the input data using the estimated mean and variance during training into Gaussian distribution with mean $\beta$ and variance $\gamma[1]$, where $\beta$ and $\gamma$ are learned during back propagation. w-bn redistributes each batch normalization layer by increasing the weights of the targeted classes when estimating the mean and variance of the input data for each batch norm layer. This method comes from a finding that when doing so, the decision boundaries between the target classes and non-target classes can be shifted towards the target classes. To demonstrate this phenomenon, Figure 5(a) shows a toy 2D dataset composed of three classes. Figure 5(b) shows the decision boundary of a well-trained simple ResNet model and Figure 5(c) shows the decision boundary of the model retrained via w-bn. It is noticeable that the decision boundary of class 2 expand over class 0 and class 1.

With the decision boundaries shifting towards the target classes, there are four consequences. First, the DNN’s correct prediction on non-target classes will not be mispredicted to the non-target classes. Second, the DNN’s wrong prediction on non-target classes to target classes can potentially be assigned correctly. Third, the DNN’s correct prediction on the target classes might be mispredicted to non-target classes. Fourth, the DNN’s wrong prediction on the target classes to other target classes might be mispredicted to non-target classes.

Consequence four will reduce the confusion/bias error. Consequence two benefit while consequence three and four will hurt the overall accuracy. The overall consequence will reduce confusion/bias error and have an uncertain influence on the overall accuracy. Empirically, we find the later depends on specific problem and hyper-parameter tuning.

Next, we formally introduce w-bn in Figure 6. We first denote $x$ to be a regular batch of images and $x^{target}$ to be a batch of images sampled only from the target classes. (a) shows a traditional BN layer and (b) shows a reweighted BN layer. The main differences are that the weighted BN layer passes an extra batch of the target classes and assigns more weights to those data (controlled using a hyper-parameter $\rho \in [0, 1]$) when estimating the BN statistics (i.e. batch mean $E$ and batch variance $Var$) in the DNN’s forward pass. It should be noted that during the back-propagation, only the loss coming from the regular batch (highlighted in dashed red box) is considered. This is because if the extra sampled input data from the target classes are considered in the optimization, this part will be similar to w-aug but we want to evaluate the influence of w-aug and w-bn separately.

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3.3.1 **Fixing confusion error.** The pair of confused classes $A$ and $B$ are the target classes. As we discussed earlier, many instances confused between $A$ and $B$ will be predicted to non-target classes. Consequently, the confusion between class $A$ and $B$ drops.

3.3.2 **Fixing bias error.** The biased triplet of classes $A$, $B$, and $C$ will be included in the target class. The decision boundaries of all the three classes will contract and a subset of images mispredicted from one target class to another is likely to be predicted to other non-target classes. As a result, both confusions between $A$ and $C$, and $B$ and $C$ tend to drop. It follows that the bias will be reduced as long as the two pairs of confusion drop at relatively similar rate.

3.3.3 **Applicable scenario.** Fine-tuning is allowed and the DNN model has batch norm layers.
3.3.4 Extension to multiple pairs/triplets. We consider all the involved classes in the pairs/triplets as the target classes.

3.4 Regularize Output: Weighted Output Smoothing (w-os)

The weighted output smoothing method tries to reduce a DNN’s confusion/bias error when fine-tuning the model is not possible. Since the model itself cannot be updated, only its output can be changed. The key observation is that misclassified images are more likely to have lower confidence in the last layer. Thus, to reduce the confusion/bias error of the target classes, we can make those low confident DNN’s prediction on the target classes to be predicted to the most confident non-target classes instead. The consequences are essentially similar to w-bn which contracts the decision boundaries of the target classes. Based on similar reasoning, the confusion/bias errors are likely to be reduced while the impact on the overall accuracy depends on the specific case.

Note that similar prediction scaling methods have been used for other purposes like calibrating a DNN’s prediction to be consistent with its true correctness likelihood[22] or post-processing a DNN’s prediction to improve a DNN’s group-level fairness[24]. The main difference is that the concrete scaling strategies are developed differently for different purposes. For example, the post-processing method proposed in [24] assigns different thresholds to each sensitive group for a binary classifier’s to mitigate equalized odds/opportunity. The thresholds are set to make trade-off between prediction accuracy and fairness criteria. In contrast, we apply different levels of smoothing for target classes to make trade-off between accuracy and confusion/bias errors.

We denote the last layer’s output of a given input $x$ to be $p(x)$, which is a $m$ (i.e. the number of classes) dimensional vector. Each field of $p(x)$ is positively correlated with the prediction probability of the class corresponding to that field.

3.4.1 Fixing confusion error. For single-label classification, w-os multiplies the target class prediction probability $p(x)_t$ by a specified parameter $\rho \in [0, 1]$ for images classified into any of the target classes $A$ and $B$; for multi-label classification, w-os multiplies the target class prediction probability $p(x)_t$ by $\rho$ for images predicted to have both target classes $A$ and $B$.

3.4.2 Fixing bias error. For single-label classification, w-os multiplies the target classes prediction probability $p(x)_t$ by $\rho$ for images predicted to be any of the target classes $A$, $B$, and $C$; for multi-label classification, w-os multiplies the target classes prediction probability $p(x)_t$ by $\rho$ for images predicted to have the classes $A$ and $C$ or the classes $B$ and $C$.

3.4.3 Applicable Scenario. We only have access to a model’s last layer output.

3.4.4 Extension to multiple pairs/triplets. We consider all the involved classes in the pairs/triplets as the target classes.

3.5 Regularize Loss: Weighted Loss (w-loss)

The weighted loss method fine-tunes the given DNN model with more weights in the loss function assigned to images contributing to the confusion/bias error. Intuitively, since the model takes more loss when making mistakes on those contributing to the confusion/bias error, it is likely to correctly predict those even at the sacrifice of the overall accuracy to some extent. This method is similar to the proposed class-balanced loss in [10] which increase the weight of the minority classes to address the class imbalance problem. The key difference is that the class-balanced loss increases the weights of the loss for those minority classes while w-loss increases the weights of confused samples / bias samples since the former aims to maximize the class-balanced accuracy while the latter aims to mitigate confusion/bias errors of the target classes. We next provide the new loss functions for fixing confusion and bias error respectively.
3.5.1 Fixing confusion error. Denote $Y_{\text{target}} = \{A, B\}$. The loss function is defined as:

$$\text{Loss}_{r1} = \rho \mathbb{E}_{(x, y) \sim D} L(f(x), y) + (1 - \rho) \mathbb{E}_{(x, y) \sim D(Y_{\text{target}})} L(f(x), y)$$

where the probability density function for the distribution $D(Y_{\text{target}})$ is

$$pdf'(X, Y) = \begin{cases} 
  pdf(X, Y), & \text{if } (x, y) \sim D \text{ s.t. } y \in Y_{\text{target}} \text{ and } f(x) \neq y \text{ and } f(x) \in Y_{\text{target}}. \\
  0, & \text{otherwise}
\end{cases}$$

and $\rho \in [0, 1]$ is the hyper-parameter balancing the two objectives. Intuitively, the DNN model is encouraged to better differentiate between $A$ and $B$ compared with differentiating among other classes in general.

3.5.2 Fixing bias error. The loss function is defined as:

$$\text{Loss}_{r1} = \rho \mathbb{E}_{(x, y) \sim D} L(f(x), y) + (1 - \rho) \mathbb{E}_{(x, y) \sim D(Y_{\text{target}})} L(f(x), y) + \mathbb{E}_{(x, y) \sim D(Y_{\text{target}}^*)} L(f(x), y) + \mathbb{E}_{(x, y) \sim D(Y_{\text{target}}^-)} L(f(x), y)$$

where $Y_{\text{target}}^* = \{A, C\}$ and $Y_{\text{target}}^- = \{B, C\}$. This loss function encourages the DNN model to better differentiate between $A$ and $C$ as well as $B$ and $C$ compared with differentiating among other classes in general.

3.5.3 Applicable Scenario. Fine-tuning is allowed.

3.5.4 Extension to multiple pairs/triplets. For each pair(triplet), we add one(two) extra term(terms) into the second half of the loss function and divide this part by the number of pairs(triplets).

3.6 Regularize Loss: Weighted Distance-Based Regularization (w-dbr)

The distance-based regularization method leverages the class-level representation and adds an extra regularization term in the loss function to balance the distance among the target classes in the representation space under a defined metric during the fine-tuning. The insight here is that the closer the two classes representations are, the more confused the model is between the two classes[68].

Given a class $A$, we define its class-level representation

$$P_{\text{new}}(A) = \frac{[S(n_1), S(n_2), ..., S(n_t)]}{N}$$

where $S(n_i)$ is the sum of each output of neuron $n_i$, given $N$ input images. Then, we define the distance metric between two classes $A$ and $B$ as:

$$D_{\text{new}}(A, B) = ||(P_{\text{new}}(A), P_{\text{new}}(B))||_2$$

3.6.1 Fixing confusion error. We define a new loss:

$$\text{Loss}_{\text{dbr-conf}} = \rho \text{Loss}_{\text{orig}} - (1 - \rho) D_{\text{new}}(A, B)$$

where $\rho \in [0, 1]$ trades off the original loss and the new distance-based regularization. In essence, the regularization term encourages a larger separation of the centroids of the two classes $A$ and $B$ in the representation space.
3.6.2 Fixing bias error. Similarly, we define a new loss for reducing bias:

\[ \text{Loss}_{\text{dr-bias}} = \rho \text{Loss}_{\text{orig}} + (1 - \rho) \text{abs}(D_{\text{new}}(A, C) - D_{\text{new}}(B, C)). \]

The regularization term balances the difference between the centroid distance between class A and C, and centroid distance between class B and C in the representation space such that the relative distances from A to B and C are similar.

3.6.3 Applicable Scenario. Fine-tuning is allowed.

3.6.4 Extension to multiple pairs/triplets. For each pair(triplet), we add one(two) extra term(terms) into the second half of the loss function and divide this part by the number of pairs(triplets).

4 EXPERIMENTAL DESIGN

4.1 Study Subjects

We evaluate the proposed method for single-label and multi-label DNN-based classifications including six combinations of five DNN architectures and four datasets. For each combination, we choose highly confused pair/biased triplet, those potentially have greater ethical implications, or randomly chosen pair/triplet having non-zero confusion/bias as the target using DeepInspect\[68\].

Datasets: We conduct our experiments on two single-label image classification datasets, CIFAR-10, CIFAR-100 and two multi-label image classification datasets, MS-COCO\[38\] and MS-COCO gender\[84\].

- CIFAR-10: consists of 50,000 training and 10,000 testing 32x32 color images. It has 10 classes and 6,000 images per class.
- CIFAR-100: consists of 50,000 training and 10,000 testing 32x32 color images. It has 100 classes and 600 images per class.
- MS-COCO: consists of 80783 training images and 40504 validation images. Each image labeled a subset of 80 objects.
- MS-COCO gender: same as MS-COCO but with the person class split into man and woman classes\[84\].

Architectures: We evaluate our repairing performance on five different convolutional neural networks\[26, 63\].

- ResNet-18: ResNet-18 is trained on CIFAR-10 dataset. The model is trained using the training scripts from CutMix\[79\]. The training takes 300 epochs and the repairing takes 60 epochs for methods requiring fine-tuning. The initial learning rate is 0.1 and is multiplied by 0.1 after 50% and 75% training epochs respectively.
- VGG11_BN: VGG11_BN is a variant of VGG11 model with batch normalization layers \[63\]. We train a VGG11_BN model on CIFAR-10 dataset in the same way as above.
- MobileNetv2: MobileNetv2 is a popular model tailored for mobile and resource constrained environments \[60\]. We train it on CIFAR-10 dataset in the same way as above.
- ResNet-34: ResNet-34 is trained on CIFAR-100 dataset. The model is trained in the same way as above.
- ResNet-50: Following Zhao et al\[84\], we train ResNet-50 models for both MS-COCO and MS-COCO gender datasets. Both models are trained for 12 epochs and are repaired by retraining of another 6 epochs for methods requiring fine-tuning.

Table 1 summarizes our study subjects including the details of all the datasets and models used.

Pairs/Triplets Selection: In this work, we mainly focus on mitigating the user selected confusion pairs / biased triplets. We next discuss how we choose the pairs/triplets used for the experiments.
Table 1. **Study Subjects**

| Classification Task | Dataset | Name         | #classes | Models                       | #Params       | #Layers | Reported Accuracy |
|---------------------|---------|--------------|----------|------------------------------|---------------|---------|-------------------|
| Multi-label         | COCO    | [38]         | 80       | ResNet-50[26]                | 23,671,952    | 174     | 0.6603*           |
|                     | COCO gender | [84]        | 81       | ResNet-50[26]                | 23,674,001    | 174     | 0.6691*           |
| Single-label        | CIFAR-100 | [33]        | 100      | ResNet-34 [79]               | 336,244       | 101     | 0.6941†           |
|                     | CIFAR-10 | [33]         | 10       | ResNet-18 [79]               | 127,642       | 41      | 0.8747††          |
|                     |         | VGG11-BN [63]|         |                              | 9,756,426     | 36      | 0.9175††          |
|                     |         | MobileNetv2 [60] |       |                              | 2,296,922     | 115     | 0.9420††          |

* reported in mean average precision, † reported in mean accuracy

First, for the selection of confused pairs:
- COCO, CIFAR-100, CIFAR-10: we choose the most confused pairs in terms of \( \text{type1conf/type2conf} \) (defined in Section 2.2).
- COCO gender: since the major difference between COCO gender and COCO is that the person class is categorized into man and woman and the confusion related to gender are of high interest in the study of fairness, we choose pairs with respect to gender. In particular, we choose the “woman-handbag” pair which is a relatively (but not the most) confused pair.
- COCO two pairs and CIFAR-10 two pairs: we keep the original pair and choose another one randomly among the pairs with non-zero confusions with each other.

Second, for the selection of biased triplets:
- COCO, CIFAR-100, CIFAR-10: we keep the original two classes in the confused pair and randomly choose a third class such that the bias in terms of \( \text{cd} \) (defined in Section 2.2.1) is larger than 0.
- COCO gender: with the same motivation as in choosing the confused pairs, we choose the “man-woman-skis” triplet which involves both man and woman as well as being a highly biased triplet.

### 4.2 Baseline

The baselines we use are the original models and the fine-tuned original model which have been properly trained as discussed in Section 4.1. We did not compare with methods for instance-wise fixing or dataset-wise fixing because they target different problems. We also did not compare with methods developed for class imbalance directly since our methods w-aug, w-os, w-loss can already be regarded as the adaptations of those methods for the current problem setting.

### 4.3 Evaluations Metrics

For either fixing the confusion error or bias error, the goal is to reduce error while maintaining the model’s overall accuracy.

#### 4.3.1 Rank Sum

Since there are two goals i.e. high accuracy and low confusion/bias a model tries to achieve, for comparison purpose, we rank each fixed model (including the original model) by accuracy and confusion respectively. Next, we sum up the two ranks for each model and compare the rank sums. The model with the smallest rank sum is considered the one that achieves the best trade-off between accuracy and confusion/bias. Note that we choose this simple metric to give the most intuitive performance comparisons. A more complicated method like weighted combination of accuracy and confusion/bias can also be used.
4.3.2 Statistical Tests. To validate the statistical significance of the results, we additionally conduct Wilcoxon rank-sum test [9] and Vargha-Delaney effect size test [3, 70] between the proposed methods and the baseline orig-ft in terms of both accuracy difference and confusion difference. To highlight the results, we only apply the tests for confusion difference on those already having smaller average confusion than orig-ft. Next, we only further apply the tests for accuracy difference for those methods that have statistically significantly (at least at the 0.10 level) lower confusion than orig-ft. Ideally, when compared with orig-ft, a fixed model should have statistically significantly smaller confusion and no significant lower accuracy at the same time. If not stated otherwise, we use 0.05 as the default significance level.

4.4 Hyper-parameter Selection
To show the influence of hyper-parameter choice on each method’s performance as well as selecting the best one, under each setting, we apply a grid search on \{0.1, 0.3, 0.5, 0.7, 0.9\} by running each method with each hyper-parameter one times and compare the results. Since w-os is a very fast post-processing method but tends to have very different scales across datasets, for datasets (CIFAR-10, CIFAR-100) where w-os(0.1) does not reduce confusion/bias much, we further try 0.01, 0.001, and 0.0001 in order until we have found one that can reduce confusion/bias by at least 25% when compared with that of orig-ft. We present the detailed results of hyper-parameter search in Appendix A. Since there are two objectives to optimize: mitigating confusion for the target classes and keeping the overall accuracy of all classes, for each method, we apply the following procedures to select the best performing one:

- If there are hyper-parameters that result in the models having confusion at least 25% (one can change this number according to one’s need) smaller than the original model, among them, select the one with the highest overall accuracy.
- Otherwise, if there are hyper-parameters that result in confusion decreases or stays the same, among them, select the one with the highest overall accuracy.
- Otherwise, among all the hyper-parameters, select the one with the highest overall accuracy.

If the selected hyper-parameter does not result in higher accuracy and lower confusion when compared with the original model, and such a hyper-parameter exists for the current method, this initially not selected hyper-parameter is additionally selected.

4.5 Research Questions.
We investigate two research questions to evaluate WR for target bug fixing of DNNs:

- **RQ1.** Can WR fix confusion errors of DNN models for both single-label classification and multi-label classification effectively?
- **RQ2.** Can WR fix bias errors of DNN models for both single-label classification and multi-label classification effectively?

5 RESULTS

**RQ1. Fixing Confusion Error**  We first explore if the proposed methods can reduce confusion errors effectively. In particular, we evaluate them on two settings for the task of multi-label classification and four settings for the task of single-label classification. We run each method with the selected hyper-parameter(s) (based on the procedure in Section 4.4) for five times to compare with each other as well as the baselines, and apply statistical tests to check significance.

Table 2 shows the main results for reducing confusion following the previously mentioned procedures, where we highlight the top2 (or top3 if tied) methods having the smallest rank sums. In summary, under every setting, at least two methods can achieve lower confusion while preserving
decent overall accuracy (or mean average precision). For example, w-os can almost always decrease the confusion more than 25% under every setting while maintaining accuracy at a reasonable level (no more than 1%).

![Image](image-url)

**Table 2. Results on Confusion**

| Dataset | Model  | Target Classes | Method | Accuracy | Confusion | Acc Rank | Conf Rank | Rank Sum | Acc W | Acc VD | Conf W | Conf VD |
|---------|--------|----------------|--------|----------|-----------|----------|-----------|----------|-------|-------|--------|--------|
| COCO *  | ResNet-50 | person, bus    | orig-ft| 0.6604   | 0.2381    | 5        | 7        | 12       |       |       |        |        |
|         |        |                | w-aug(0.9) | 0.6614 ± 0.0003 | 0.2329 ± 0.0084 | 2 | 6 | 8 | | | | |
|         |        |                | w-bn(0.9) | 0.6611 ± 0.0004 | 0.2622 ± 0.0097 | 4 | 8 | 12 | | | | |
|         |        |                | w-loss(0.9) | 0.6617 ± 0.0005 | 0.1875 ± 0.0121 | 4 | 5 | 10 | | | | |
|         |        |                | w-dbr(0.9) | 0.6613 ± 0.0002 | 0.2144 ± 0.0094 | 3 | 6 | 9 | | | | |
|         |        |                | w-os(0.7) | 0.6604 ± 0.0004 | 0.0677 ± 0.0012 | 3 | 1 | 6 | | | | |
|         |        |                | w-os(0.9) | 0.6602 | 0.1159 | 8 | 2 | 10 | | | | |
|         |        |                |          | 0.6604 | 0.203 | 5 | 3 | 10 | | | | |
| COCO gender* | ResNet-50 | handbag, woman | orig-ft | 0.6701 | 0.0402 | 5 | 5 | 10 | | | | |
|         |        |                | w-aug(0.9) | 0.6707 ± 0.0004 | 0.0422 ± 0.0069 | 2 | 6 | 8 | | | | |
|         |        |                | w-bn(0.9) | 0.6707 ± 0.0003 | 0.0225 ± 0.0059 | 2 | 4 | 9 | | | | |
|         |        |                | w-loss(0.7) | 0.6700 ± 0.0002 | 0.0225 ± 0.0059 | 2 | 5 | 9 | | | | |
|         |        |                | w-dbr(0.9) | 0.6700 ± 0.0004 | 0.0725 ± 0.0079 | 7 | 1 | 13 | | | | |
|         |        |                | w-os(0.7) | 0.6698 | 0.0044 | 7 | 1 | 8 | 0.009 | 0.00 | 0.00 | 0.00 |
| CIFAR-100 | ResNet-34 | girl, woman | orig-ft | 0.6998 | 0.155 | 4 | 7 | 11 | | | | |
|         |        |                | w-aug(0.3) | 0.7051 ± 0.0025 | 0.1430 ± 0.0179 | 4 | 5 | 10 | | | | |
|         |        |                | w-bn(0.9) | 0.7034 ± 0.0013 | 0.1420 ± 0.0192 | 2 | 5 | 10 | | | | |
|         |        |                | w-loss(0.9) | 0.6956 ± 0.0108 | 0.1440 ± 0.0074 | 6 | 11 | | | | | |
|         |        |                | w-dbr(0.9) | 0.6818 ± 0.0046 | 0.1210 ± 0.0082 | 7 | 9 | 12 | | | | |
|         |        |                | w-os(0.1) | 0.6976 | 0.105 | 5 | 9 | 11 | | | | |
| CIFAR-10 | ResNet-18 | cat, dog | orig-ft | 0.8747 | 0.0960 | 5 | 5 | 10 | | | | |
|         |        |                | w-aug(0.7) | 0.8779 ± 0.0009 | 0.0993 ± 0.0041 | 5 | 5 | 10 | | | | |
|         |        |                | w-bn(0.7) | 0.8778 ± 0.0016 | 0.0966 ± 0.0017 | 6 | 7 | 9 | | | | |
|         |        |                | w-loss(0.9) | 0.8489 ± 0.0007 | 0.0671 ± 0.0067 | 3 | 6 | 9 | | | | |
|         |        |                | w-dbr(0.9) | 0.8761 ± 0.0005 | 0.1003 ± 0.0013 | 3 | 7 | 9 | | | | |
|         |        |                | w-os(0.1) | 0.8654 | 0.071 | 2 | 6 | 9 | | | | |
| VGG-11 with BN | cat, dog | orig-ft | 0.9197 | 0.081 | 1 | 6 | 7 | | | | |
|         |        |                | w-aug(0.9) | 0.9180 ± 0.0020 | 0.0757 ± 0.0070 | 4 | 8 | 10 | | | | |
|         |        |                | w-bn(0.7) | 0.9187 ± 0.0011 | 0.0724 ± 0.0040 | 3 | 6 | 9 | | | | |
|         |        |                | w-loss(0.9) | 0.9070 ± 0.0011 | 0.0539 ± 0.0032 | 2 | 8 | 9 | | | | |
|         |        |                | w-dbr(0.9) | 0.9129 ± 0.0019 | 0.0866 ± 0.0026 | 7 | 12 | | | | | |
|         |        |                | w-os(0.001) | 0.7402 ± 0.0400 | 0.0908 ± 0.0288 | 9 | 16 | | | | | |
|         |        |                | w-os(0.9) | 0.9059 | 0.0525 | 1 | 6 | 7 | | | | |
| MobileNetV2 | cat, dog | orig-ft | 0.9420 | 0.0565 | 4 | 5 | 10 | | | | |
|         |        |                | w-aug(0.5) | 0.9384 ± 0.0012 | 0.0632 ± 0.0045 | 1 | 4 | 5 | | | | |
|         |        |                | w-bn(0.7) | 0.9159 ± 0.0018 | 0.0357 ± 0.0030 | 8 | 10 | | | | | |
|         |        |                | w-loss(0.9) | 0.9341 ± 0.0012 | 0.0667 ± 0.0064 | 6 | 14 | | | | | |
|         |        |                | w-dbr(0.9) | 0.9397 ± 0.0014 | 0.0571 ± 0.0033 | 3 | 8 | 8 | | | | |
|         |        |                | w-os(0.001) | 0.9226 | 0.0360 | 7 | 9 | 12 | | | | |
|         |        |                | w-os(0.3) | 0.9420 | 0.0415 | 1 | 3 | 4 | 0.009 | 0.00 | 0.00 | 0.00 |

* reported in mean average precision; Acc: Accuracy; Conf: Confusion; VD: Vargha-Delaney effect size test; W: Wilcoxon rank-sum test; n: negligible; s: small; m:medium; l: large

For the multi-label classification task, both w-loss and w-bn achieve good trade-off between mean average precision and confusion in terms of the rank sum. On both the COCO and COCO gender datasets, compared with orig-ft, at the 0.05 significance level, both w-loss and w-bn reduce confusion significantly with large effect size and do not significantly decrease the overall mean average precision at the same time. For example, on COCO, compared with orig-ft, w-loss(0.9) has much...
smaller average confusion between person and bus (0.1244 VS 0.2329) and its mean average precision is only smaller by 0.0001 which is not statistically significant.

For the single-label classification task, w-os usually achieves good trade-offs between accuracy and confusion. It is among the top2 in terms of the rank sum in three out of the four settings. On CIFAR-100, orig-ft is the best in terms of rank sum. In order to mitigate confusion, accuracy has to be sacrificed. This can be seen from w-os(0.1) where the average confusion decreases from 0.1430 to 0.105 but the average accuracy drops from 0.7051 to 0.6976. Both differences are statistically significant at the 0.01 level. In the setting of CIFAR-10 and ResNet-18, and CIFAR-10 and VGG-11 with BN, w-dbr(0.9) and w-aug(0.9) are ranked the top respectively. They both achieve significantly smaller confusion while maintaining the accuracy with no significant drop. On CIFAR-10 with MobileNetV2, w-os(0.3) is ranked the top and has both significant smaller confusion and higher accuracy when compared with orig-ft.

Under all the settings, both w-os and w-bn can always decrease confusion significantly, and are ranked among the top ones in many settings. Although w-loss works very well on COCO and COCO gender, it works poorly on CIFAR-10 and CIFAR-100. A deeper exploration of the retraining process reveals that its retraining processes on CIFAR-10 and CIFAR-100 tend to be very unstable. For example, on CIFAR-100, it tends to misclassify dog to cat much more frequently at one epoch and the reverse at another. w-aug does not perform well in general. This is potentially because the cause of confusion is not due to the lack of instances belonging to the target classes. This is particularly true for CIFAR-100 and CIFAR-10 where all the classes have the same number of instances for each class. w-dbr can reduce confusion for COCO, CIFAR-100 and CIFAR-10 but fails to do so on COCO gender. One possibility is that the confusion between handbag and woman is already relatively small and the class centroids between woman and handbag are far away from each other so the extra loss regularization term does not help much to reduce the confusion further.

Figure 7 shows some examples of the fixed confusion instances. On the CIFAR-10 dataset and ResNet-18 combination, Figure 7(a)-(b) show two cat images that were classified to dog by the original model. After applying w-dbr, they are correctly predicted to cat. Figure 7(c)-(d) show two dog images that were classified to cat by the original model. After applying w-dbr, they are correctly predicted to dog. Similarly, on the CIFAR-100 dataset and ResNet-34 combination, Figure 7(e)-(f) show two girl images that were classified to woman by the original model. After applying w-dbr, they are correctly predicted to girl. Figure 7(g)-(h) show two woman images that were classified to girl by the original model. After applying w-dbr, they are correctly predicted to woman. On the COCO dataset and ResNet-50 combination, Figure 7(i)-(j) show two images that contain only person but the original model mispredicts the presence of bus. After applying w-loss, the model correctly predicts the presence of person without false positively predicting the presence of bus. Similarly, Figure 7(k)-(l) show two images with only bus in them but the original model false positively predicts the presence of person as well. After applying w-loss, the model can correctly predict the presence of bus while not falsely predicting the presence of person.

Next, we evaluate if the proposed methods can be applied to fix confusion errors among multiple pairs at the same time by applying the proposed methods to fix confusions of two pairs (one top confused pair and one randomly picked confused pair) on CIFAR-10 and COCO. Table 3 shows the results. On COCO, w-loss(0.9) achieves the best trade-off between accuracy and confusion in terms of rank sum. Compared with orig-ft, it has smaller confusion at 0.01 significance level and no significant accuracy drop. On CIFAR-10, w-bn(0.9) achieves the best trade-off. However, compared with orig-ft, it does not have significantly smaller confusion. In contrast, w-dbr(0.9) has smaller confusion than orig-ft at the 0.1 significance level and no significant accuracy drop.

Next, besides the overall accuracy and the confusion of the target pair as shown in Table 2 and Table 3, we explore more fine-grained impact of applying the proposed methods. We showed the
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Fig. 7. Fixed confusion errors on CIFAR-10 ((a)-(d)), CIFAR-100 ((e)-(h)), and COCO ((i)-(l)) respectively.

Table 3. Results on Confusion (Two Pairs)

| Dataset | Model     | Target Classes | Method              | Accuracy | Confusion | Acc Rank | Conf Rank | Rank Sum | Acc W | Acc VD | Conf W | Conf VD |
|---------|-----------|----------------|---------------------|----------|-----------|----------|-----------|----------|-------|--------|--------|---------|
| COCO *  | ResNet-50 | (person, bus)  | orig                | 0.6604   | 0.2013    | 5        | 5         | 10       |       |        |        |         |
|         |           | (mouse, keyboard) | orig-ft              | 0.6614±0.0003 | 0.2266±0.0088 | 1 | 6 | 7 |       |        |        |         |
|         |           |                  | w-aug(0.9)          | 0.6609±0.0004 | 0.2305±0.0140 | 3 | 7 | 10 |       |        |        |         |
|         |           |                  | w-bn(0.7)           | 0.6606±0.0002 | 0.1234±0.0081 | 4 | 2 | 6 | 0.009 0.0(l) | 0.009 0.0(l) |        |         |
|         |           |                  | w-loss(0.9)         | 0.6611±0.0003 | 0.1307±0.0153 | 2 | 5 | 5 | 0.251 0.280(m) | 0.009 0.0(l) |        |         |
|         |           |                  | w-dbr(0.9)          | 0.6589±0.0002 | 0.1629±0.0067 | 7 | 4 | 11 | 0.009 0.0(l) | 0.009 0.0(l) |        |         |
|         |           |                  | w-os(0.7)           | 0.6595    | 0.0968    | 6 | 1 | 7 |       |        |        |         |
| CIFAR-10| ResNet-18 | (cat, dog)       | orig                | 0.8774±0.0010 | 0.0680±0.0025 | 1 | 8 | 9 |       |        |        |         |
|         |           |                  | w-aug(0.7)          | 0.8764±0.0012 | 0.0678±0.0011 | 1 | 7 | 11 |       |        |        |         |
|         |           |                  | w-bn(0.5)           | 0.8471±0.0004 | 0.0495±0.0007 | 8 | 1 | 9 | 0.009 0.0(l) | 0.009 0.0(l) |        |         |
|         |           |                  | w-bn(0.9)           | 0.8772±0.0008 | 0.0649±0.0028 | 2 | 2 | 4 | 0.175 0.240(l) |        |        |         |
|         |           |                  | w-loss(0.9)         | 0.8755±0.0022 | 0.0670±0.0034 | 5 | 10 |       | 0.465 0.360(s) | 0.076 0.160(l) |        |         |
|         |           |                  | w-dbr(0.9)          | 0.8770±0.0013 | 0.0650±0.0034 | 3 | 6 | 10 | 0.009 0.0(l) | 0.009 0.0(l) | 0.602 0.400(s) |         |
|         |           |                  | w-os(0.9)           | 0.8749    | 0.0660    | 6 | 4 | 10 |       |        |        |         |

* reported in mean average precision; Acc: Accuracy; Conf: Confusion; VD: Vargha-Delaney effect size test; W: Wilcoxon rank-sum test; n: negligible; s: small; m: medium; l: large

confusion matrices for all the classes under different methods under the setting of CIFAR-10 and VGG-11 with BN in Figure 8. In Figure 9, we additionally visualize the confusion from the target classes to other classes for all the methods. In both the original model and the fine-tuned original model, dog(label 5) is highly confused with cat(label 3) than any other classes. Both w-os and w-bn reduce the confusion between dog and cat from both directions. As the trade-off, the confusion
between dog/cat and other classes increase. This is consistent with the intuition that both methods contract the decision boundaries of the target classes. It also worth noting that w-bn provides a relatively uniform distribution of the confusion among all the pairs after the fixing. This might be a desirable property if a user does not want to overburden one particular non-target class in terms of the confusion distribution. The result also suggests a future exploration direction of our method: by adjusting hyper-parameters, one can optimize the model such that the maximum pair-wise confusion is the lowest. w-aug similarly decreases the confusion between dog and cat but to a smaller extent. At the same time, it also increases less of the confusion for other pairs. Although w-dbr reduces the confusion between dog and cat, the main reduction comes from the zero confusion from dog to cat after w-dbr. The confusion from cat to dog actually increases. Besides, it increases the model’s confusion from many classes to dog and frog (as shown in Figure 8f). w-loss reduces some confused instances from cat to dog, it fails to do so for instances from dog to cat. The overall observation is that there is no free lunch for reducing the confusion for the target classes, the confusion for others has to be sacrificed to some extent.

Since w-os can be applied when no training data is available or retraining is allowed and can reduce confusion by a significant amount (>25%) while only slightly sacrificing the overall performance (<1%) under every setting, we conduct a more comprehensive ablation study on its hyper-parameter $\rho$ to explore its trade-off between confusion and accuracy. Figure 10 shows the results. Note that by decreasing $\rho$, the confusion decreases and accuracy decrease at the same time. Thus, a user can decide what parameter to use depending on the significance of accuracy and confusion. The influence of the hyper-parameter for other methods can also be found in Appendix A.

**Result 1:** The proposed method WR can reduce confusion errors for both single-label and multi-label image classification. Under every setting, at the 0.05 significance level, compared with the fine-tuned original model baseline, at least one fixing method can achieve significant lower confusion. Besides, under four out of six settings, the methods also do not have significant accuracy drop at the same time. Under the rest two settings, the sacrificed accuracy is less than 1%. The proposed method’s also generalize to reduce confusion errors for multiple pairs.

**RQ2. Fixing Bias Error** In this RQ, we explore if the proposed methods can fix bias errors. The settings and procedures are similar to those for evaluating confusion error fixing. Table 4 shows the results under different settings. In summary, the general trend is similar to fixing the confusion error. Under every setting, at least two of the proposed methods can achieve lower bias while preserving decent overall accuracy (or mean average precision).

For the multi-label classification task, w-loss strikes the best trade-off between mean average precision and bias in terms of the rank sum. On both the COCO and COCO gender datasets, at the 0.05 significance level, compared with orig-ft, w-loss has lower bias with large effect size and does not have significant mean average precision drop. For example, on COCO, compared with orig-ft, w-loss(0.9) has much lower average bias between person and clock with respect to bus (0.1240 VS 0.2314) while only has 0.0001 smaller mean average precision on average.

For the single-label classification task, w-os is ranked among the top2 under every setting. However, compared with orig-ft, at the 0.05 significance level, although w-os can always reduce bias, it has to sacrifice the accuracy as well. Under the setting of CIFAR-100 and ResNet-34, and CIFAR-10 and MobileNetv2, in order to reduce bias, any of the proposed method has to sacrifice accuracy. Under the setting of CIFAR-10 and ResNet-18, and CIFAR-10 and VGG-11 with BN, at the 0.05 significance level, w-bn(0.9) and w-aug(0.3) can reduce bias while still maintain the accuracy.
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For example, on CIFAR-10 and ResNet-18, compared with orig-ft, w-bn(0.9) has lower bias (0.0619 VS 0.0806) with large effect size and has only accuracy drop by 0.0002 which is not statistically significant.

Similar to fixing confusion errors, under all the settings, w-os and w-bn work reasonably well and give decent trade-off between accuracy and bias. w-bn can reduce bias significantly in most settings but tends to be slightly worse than w-os overall. w-loss works very well for the multi-label

Fig. 8. **Confusion matrices of the VGG11-BN after applying different methods on it.**
classification task but not for the single-label classification task. w-aug performs much better on CIFAR-100 and CIFAR-10 than on COCO and COCO gender. w-dbr can reduce bias for COCO, COCO gender and CIFAR-100 but fails to do so for CIFAR-10.

Figure 7 shows two examples of the fixed bias instances under the setting of COCO gender and ResNet-50. Figure 11(a) shows an image containing a woman and a skis but the original model classifies the woman to man. After applying w-loss, the model correctly predicts the presence of woman and skis. Figure 11(b) shows an image containing several woman, man and skis while the original model only predicts the presence of only man and skis while missing woman. After fixing the model using w-loss, the model successfully predicts the presence woman, man and skis.

**Result 2:** The proposed method WR can effectively reduce bias errors for both single-label and multi-label image classification. Under every setting, compared with the fine-tuned original model baseline, at least one fixing method can achieve significant lower bias. Besides, under four out of six settings, the method does not have significant accuracy drop at the same time. Under the rest two settings, significant lower bias can also be achieved but accuracy has to be sacrificed for 1% and 5% respectively.
| Dataset          | Model     | Target Classes | Method     | Accuracy | Bias  | Acc Rank | Bias Rank | Rank Sum | Acc W | Acc VD | Bias W | Bias VD |
|------------------|-----------|----------------|------------|----------|-------|----------|----------|----------|-------|-------|--------|--------|
| COCO *           | ResNet-50 | bus, person,    | orig-ft    | 0.6604   | 0.2366| 4        | 7        | 11       |       |       |        |        |
|                  |           | clock          | w-aug(0.9) | 0.6614 ± 0.0003 | 0.2314 ± 0.0084 | 6 | 7 | 7 |
|                  |           |                | w-bn(0.5)  | 0.6670 ± 0.0005 | 0.2483 ± 0.0209 | 8 | 11 | 7 |
|                  |           |                | w-loss(0.9)| 0.6575 ± 0.0005 | 0.1722 ± 0.0176 | 3 | 10 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-dbr(0.1) | 0.6613 ± 0.0002 | 0.1240 ± 0.0093 | 2 | 4 | 0.531 ± 0.380 (s) | 0.009 (l) |
|                  |           |                | w-os(0.7)  | 0.6537 ± 0.0007 | 0.1949 ± 0.0179 | 4 | 12 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-os(0.9)  | 0.6602 | 0.1131 | 6 | 1 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-os(0.9)  | 0.6604 | 0.2015 | 4 | 5 | 9 | 0.009 (l) | 0.009 (l) |
| COCO gender*     | ResNet-50 | iskiis, woman,  | orig-ft    | 0.6701   | 0.2521| 4 | 7 | 11 |
|                  |           | man            | w-aug(0.9) | 0.6708 ± 0.0002 | 0.2457 ± 0.0106 | 5 | 7 | 7 |
|                  |           |                | w-bn(0.9)  | 0.6684 ± 0.0002 | 0.1771 ± 0.0054 | 6 | 10 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-loss(0.9)| 0.6708 ± 0.0001 | 0.1370 ± 0.0207 | 3 | 5 | 0.296 ± 0.3 (s) | 0.009 (l) |
|                  |           |                | w-dbr(0.3) | 0.6677 ± 0.0003 | 0.1311 ± 0.0564 | 7 | 2 | 0.009 (l) | 0.016 (l) |
|                  |           |                | w-os(0.5)  | 0.6693 | 0.0727 | 5 | 1 | 0.009 (l) | 0.009 (l) |
| CIFAR-100        | ResNet-34 | woman, girl,    | orig-ft    | 0.7042 ± 0.0010 | 0.0680 ± 0.0164 | 4 | 7 | 9 |
|                  |           | boy            | w-aug(0.7) | 0.7051 ± 0.0011 | 0.0710 ± 0.0108 | 7 | 8 | 8 |
|                  |           |                | w-bn(0.7)  | 0.6779 ± 0.0009 | 0.0450 ± 0.0079 | 6 | 1 | 0.009 (l) | 0.028 (l) |
|                  |           |                | w-loss(0.9)| 0.7011 ± 0.0007 | 0.0700 ± 0.0190 | 5 | 8 | 4.65 ± 0.360 (s) |
|                  |           |                | w-dbr(0.1) | 0.0472 ± 0.0111 | 0.0269 ± 0.0277 | 8 | 13 | 0.009 (l) | 0.014 (l) |
|                  |           |                | w-os(0.01) | 0.6938 | 0.045 | 6 | 1 | 0.009 (l) | 0.009 (l) |
| CIFAR-10         | ResNet-18 | dog, cat, bird | orig-ft    | 0.8747   | 0.074 | 7 | 12 |       |
|                  |           |                | w-aug(0.7) | 0.8776 ± 0.0011 | 0.0806 ± 0.0441 | 9 | 8 | 9 |
|                  |           |                | w-bn(0.7)  | 0.8671 ± 0.0015 | 0.0553 ± 0.0228 | 10 | 2 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-loss(0.9)| 0.8774 ± 0.0020 | 0.0619 ± 0.0003 | 12 | 5 | 0.009 (l) | 0.012 ± 0.00 (l) |
|                  |           |                | w-dbr(0.9) | 0.8712 ± 0.0009 | 0.0295 ± 0.0287 | 16 | 9 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-os(0.01) | 0.8181 | 0.0425 | 9 | 1 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-os(0.9)  | 0.8751 | 0.063 | 4 | 8 | 0.009 (l) | 0.009 (l) |
| VGG-11 with BN   | ResNet-18 | dog, cat, bird | orig-ft    | 0.9197   | 0.0675 | 2 | 10 |       |
|                  |           |                | w-aug(0.3) | 0.9181 ± 0.0023 | 0.0603 ± 0.0074 | 10 | 6 | 10 |
|                  |           |                | w-bn(0.9)  | 0.9171 ± 0.0015 | 0.0497 ± 0.0055 | 7 | 1 | 0.251 ± 0.280 (m) | 0.047 ± 0.120 (l) |
|                  |           |                | w-loss(0.9)| 0.9133 ± 0.0017 | 0.0030 ± 0.0074 | 3 | 6 | 0.251 ± 0.280 (m) |
|                  |           |                | w-dbr(0.9) | 0.9122 ± 0.0009 | 0.0604 ± 0.0038 | 12 | 5 | 0.017 ± 0.040 (l) |
|                  |           |                | w-os(0.001)| 0.9023 | 0.041 | 8 | 1 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-os(0.7)  | 0.9198 | 0.056 | 4 | 5 | 0.117 ± 0.2 (l) |
| MobileNetv2      | ResNet-18 | dog, cat, bird | orig-ft    | 0.942    | 0.0415 | 1 | 3 | 4 |
|                  |           |                | w-aug(0.5) | 0.9384 ± 0.0012 | 0.0648 ± 0.0047 | 2 | 7 | 7 |
|                  |           |                | w-bn(0.5)  | 0.9383 ± 0.0010 | 0.0418 ± 0.0018 | 4 | 7 | 4 |
|                  |           |                | w-loss(0.1) | 0.8981 ± 0.0017 | 0.0272 ± 0.0255 | 2 | 7 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-dbr(0.9) | 0.9384 ± 0.0004 | 0.0916 ± 0.0482 | 7 | 14 | 0.009 (l) | 0.009 (l) |
|                  |           |                | w-os(0.0001) | 0.8943 | 0.0240 | 6 | 1 | 0.009 (l) | 0.009 (l) |

* reported in mean average precision; Acc: Accuracy; VD: Vargha-Delaney effect size test; W: Wilcoxon rank-sum test; n: negligible; s: small; m:medium; l: large

6 RELATED WORK

6.1 Software Repairing

Automatic software repairing is very challenging and most of existing work focus on traditional software.[53]. Traditional automatic repairing techniques include random or guided mutation of AST(Abstract Syntax Tree)[11, 17, 36, 37, 56, 62, 73, 74], static program analysis or symbolic execution/concrete execution[18, 39, 40, 54, 55, 67]. The most recent techniques involve language models training and program synthesis[23, 78]. All these techniques proposed to repair traditional
programs such as C, C++, Java or Python, cannot work on DNN based software because there is no program logic or AST in DNN models. In this paper, we propose a generic method for automatic target repairing group-wise errors in DNN based software.

6.2 DNN Testing and Repairing

An increasing number of works in SE for AI area focus on DNN testing and repairing. The testing techniques usually leverage metamorphic relation as oracle and coverage guided image transformation or perturbation for generating test cases[31, 42–44, 57, 66, 77, 86]. Data augmentation and retraining techniques are usually proposed for repairing DNN models in improving overall accuracy[45, 59, 64]. There are also works in improving robustness of models against adversarial instances[15, 19, 30, 46, 47, 49, 52, 69, 71, 72, 76, 85]. All of these papers focus on repairing instance-wise or dataset-wise errors. In contrast, our paper focuses on fixing group-wise errors.

6.3 Fairness

Fairness is an important problem from both a theoretical and a practical perspective [6, 41, 81, 82]. Related works in fairness usually define a fairness criteria and optimize the original objective while satisfying the fairness criteria [4, 12, 13, 25, 35, 51]. These properties are defined at individual [13, 32, 34] or group levels [8, 25, 80]. Our paper focuses on fixing errors based on a group-level fairness definition called bias error proposed in [68]. To the best of our knowledge, methods on repairing this bias error have not been proposed before.

7 THREATS TO VALIDITY AND DISCUSSION

There are many potential ways to fix group-level errors of DNNs. To mitigate this threat, we propose and compare the performance of five different methods along with two baselines. For each method, we set a parameter to make trade-off between accuracy and confusion/bias and show results of each method when using at least five different hyper-parameters.

There are many datasets and models, which can be used for the evaluation purpose. We choose six combinations of four widely used datasets and five for image classification. Besides, DNN training is stochastic so the results may have some fluctuations. We repeat each method with top performing hyper-parameter(s) for five times and apply statistical tests to check the significance of the results. Lastly, our method can be potentially applied to DNN models used in applications beyond image classifications such as object detection and recommendation systems. We leave that for future work.

Fig. 11. Fixed bias errors on COCO gender.
8 CONCLUSION

In this work, we propose a generic method called Weighted Regularization (WR) consists of five concrete methods that can fix group-level errors for DNNs with different trade-offs. To the best of our knowledge, this is the first work proposing, exploring and comparing target fixing methods, which can be applied in different stages of DNN retraining or inference, on repairing group-level DNN model errors. Our experimental results show that WR can effectively fix confusion and bias errors and these methods all have their pros, cons and applicable scenarios.

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## Additional Results on Hyper-Parameter Selection

In this section, we provide the detailed results of our hyper-parameter search process. The numbers colored in blue represent being selected based on the first criteria and those colored in yellow are those additionally selected based on our second criteria. The details of the selection have been discussed in Section 4.4. We then run all the selected settings for five runs with different random seeds and report the results in RQ1 and RQ2. The results presented here also reflect the influence of the choice of the hyper-parameters on each method. In particular, the smaller $\eta$ is, w-os and w-bn have lower confusion/bias and accuracy (or mean average precision). The influence of the hyper-parameters for other methods are also usually monotonic for accuracy. However, the influence on confusion/bias usually varies case by case.

### Table 5. Results on CIFAR-10 and ResNet-18

| model   | conf | bias |
|---------|------|------|
| orig    | 0.8747 | 0.0784 |
| orig-ft | 0.8775 | 0.0756 |
| w-aug 0.1 | 0.8456 | 0.0835 |
| w-aug 0.3 | 0.8731 | 0.0685 |
| w-aug 0.5 | 0.8757 | 0.0675 |
| w-aug 0.7 | 0.8777 | 0.0675 |
| w-aug 0.9 | 0.877 | 0.0675 |
| w-bn 0.1 | 0.7361 | 0.041 |
| w-bn 0.3 | 0.7916 | 0.1035 |
| w-bn 0.5 | 0.8099 | 0.077 |
| w-bn 0.7 | 0.8455 | 0.068 |
| w-bn 0.9 | 0.8757 | 0.075 |
| w-loss 0.1 | 0.4078 | 0.3325 |
| w-loss 0.3 | 0.6848 | 0.2165 |
| w-loss 0.5 | 0.7921 | 0.158 |
| w-loss 0.7 | 0.8663 | 0.072 |
| w-loss 0.9 | 0.8777 | 0.0675 |
| w-os 0.001 | 0.8056 | 0.0195 |
| w-os 0.01 | 0.839 | 0.043 |
| w-os 0.1 | 0.8664 | 0.071 |
| w-os 0.3 | 0.873 | 0.073 |
| w-os 0.5 | 0.8745 | 0.093 |
| w-os 0.7 | 0.8745 | 0.093 |
| w-os 0.9 | 0.8745 | 0.093 |
| w-dbr 0.1 | 0.7036 | 0.0112 |
| w-dbr 0.3 | 0.8238 | 0.0501 |
| w-dbr 0.5 | 0.8588 | 0.084 |
| w-dbr 0.7 | 0.8696 | 0.095 |
| w-dbr 0.9 | 0.8871 | 0.089 |

### Table 6. Results on CIFAR-10 and VGG-11 w/ BN

| model   | conf | bias |
|---------|------|------|
| orig    | 0.9197 | 0.0675 |
| orig-ft | 0.9204 | 0.076 |
| w-aug 0.1 | 0.9129 | 0.063 |
| w-aug 0.3 | 0.9161 | 0.071 |
| w-aug 0.5 | 0.9165 | 0.073 |
| w-aug 0.7 | 0.9162 | 0.077 |
| w-aug 0.9 | 0.9193 | 0.072 |
| w-bn 0.1 | 0.8168 | 0.0135 |
| w-bn 0.3 | 0.8554 | 0.012 |
| w-bn 0.5 | 0.8868 | 0.0305 |
| w-bn 0.7 | 0.9068 | 0.057 |
| w-bn 0.9 | 0.9157 | 0.072 |
| w-loss 0.1 | 0.1 | 0.1 |
| w-loss 0.3 | 0.1903 | 0.2835 |
| w-loss 0.5 | 0.5521 | 0.75 |
| w-loss 0.7 | 0.836 | 0.838 |
| w-loss 0.9 | 0.9153 | 0.110 |
| w-os 0.001 | 0.9059 | 0.0513 |
| w-os 0.01 | 0.9148 | 0.071 |
| w-os 0.1 | 0.9179 | 0.0765 |
| w-os 0.3 | 0.9199 | 0.0795 |
| w-os 0.5 | 0.9193 | 0.08 |
| w-os 0.7 | 0.9196 | 0.08 |
| w-os 0.9 | 0.9197 | 0.086 |
| w-dbr 0.1 | 0.7035 | 0.0112 |
| w-dbr 0.3 | 0.8238 | 0.0501 |
| w-dbr 0.5 | 0.8588 | 0.084 |
| w-dbr 0.7 | 0.8696 | 0.095 |
| w-dbr 0.9 | 0.8871 | 0.089 |
### Table 7. Results on CIFAR-10 and MobileNetv2

| Model  | Confusion | Bias |
|--------|-----------|------|
| Orig   | 0.942    | 0.0565 |
| Orig-ft| 0.9398   | 0.057 |
| W-aug 0.1 | 0.9392 | 0.057 |
| W-aug 0.3 | 0.9395 | 0.057 |
| W-aug 0.5 | 0.9394 | 0.057 |
| W-aug 0.7 | 0.9393 | 0.057 |

### Table 8. Results on CIFAR-100 and ResNet34

| Model  | Confusion | Bias |
|--------|-----------|------|
| Orig   | 0.6988   | 0.15 |
| Orig-ft| 0.6992   | 0.13 |
| W-aug 0.1 | 0.7021 | 0.17 |
| W-aug 0.3 | 0.707 | 0.13 |
| W-aug 0.5 | 0.7097 | 0.17 |
| W-aug 0.7 | 0.7108 | 0.17 |

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Table 9. **Results on COCO and ResNet-50**

| model     | confusion | bias | model     | confusion | bias |
|-----------|-----------|------|-----------|-----------|------|
| orig      | 0.6604    | 0.2381| orig      | 0.6604    | 0.2366|
| orig-ft   | 0.6613    | 0.2298| orig-ft   | 0.6613    | 0.2283|
| w-aug 0.1 | 0.6536    | 0.2983| w-aug 0.1 | 0.6536    | 0.3483|
| w-aug 0.3 | 0.6567    | 0.3126| w-aug 0.3 | 0.6567    | 0.3019|
| w-aug 0.5 | 0.6581    | 0.2793| w-aug 0.5 | 0.6581    | 0.2759|
| w-aug 0.7 | 0.6601    | 0.2896| w-aug 0.7 | 0.6601    | 0.2749|
| w-aug 0.9 | 0.6609    | 0.2887| w-aug 0.9 | 0.6609    | 0.2456|
| w-bn 0.1  | 0.6559    | 0.0119| w-bn 0.1  | 0.6559    | 0.121 |
| w-bn 0.3  | 0.658     | 0.0266| w-bn 0.3  | 0.658     | 0.1453|
| w-bn 0.5  | 0.6578    | 0.0549| w-bn 0.5  | 0.6578    | 0.1933|
| w-bn 0.7  | 0.6607    | 0.1266| w-bn 0.7  | 0.6607    | 0.2244|
| w-bn 0.9  | 0.6612    | 0.1699| w-bn 0.9  | 0.6612    | 0.2692|
| w-loss 0.1 | 0.661    | 0.0201| w-loss 0.1 | 0.661    | 0.0194|
| w-loss 0.3 | 0.661    | 0.0266| w-loss 0.3 | 0.661    | 0.0253|
| w-loss 0.5 | 0.661    | 0.0357| w-loss 0.5 | 0.661    | 0.0347|
| w-loss 0.7 | 0.661    | 0.0488| w-loss 0.7 | 0.661    | 0.0474|
| w-loss 0.9 | 0.661    | 0.1264| w-loss 0.9 | 0.661    | 0.1238|
| w-os 0.1  | 0.6557    | 0    | w-os 0.1  | 0.6557    | 0|
| w-os 0.3  | 0.6582    | 0    | w-os 0.3  | 0.6582    | 0|
| w-os 0.5  | 0.6599    | 0    | w-os 0.5  | 0.6599    | 0|
| w-os 0.7  | 0.6602    | 0.1159| w-os 0.7  | 0.6602    | 0.1151|
| w-os 0.9  | 0.6608    | 0.205 | w-os 0.9  | 0.6608    | 0.12015|
| w-dbr 0.1 | 0.6548    | 0.4108| w-dbr 0.1 | 0.6548    | 0.2171|
| w-dbr 0.3 | 0.6567    | 0.0978| w-dbr 0.3 | 0.6567    | 0.2729|
| w-dbr 0.5 | 0.6575    | 0.0476| w-dbr 0.5 | 0.6575    | 0.3047|
| w-dbr 0.7 | 0.6597    | 0.1226| w-dbr 0.7 | 0.6597    | 0.3369|
| w-dbr 0.9 | 0.6607    | 0.0077| w-dbr 0.9 | 0.6607    | 0.3347|

Table 10. **Results on COCO gender and ResNet-50**

| model     | confusion | bias | model     | confusion | bias |
|-----------|-----------|------|-----------|-----------|------|
| orig      | 0.6701    | 0.0402| orig      | 0.6701    | 0.2521|
| orig-ft   | 0.6709    | 0.0382| orig-ft   | 0.6709    | 0.2614|
| w-aug 0.1 | 0.6614    | 0.1435| w-aug 0.1 | 0.6614    | 0.3185|
| w-aug 0.3 | 0.6676    | 0.0565| w-aug 0.3 | 0.6676    | 0.3045|
| w-aug 0.5 | 0.67     | 0.0629| w-aug 0.5 | 0.67     | 0.2574|
| w-aug 0.7 | 0.6696    | 0.0594| w-aug 0.7 | 0.6696    | 0.2631|
| w-aug 0.9 | 0.6711    | 0.0427| w-aug 0.9 | 0.6711    | 0.2541|
| w-bn 0.1  | 0.6662    | 0    | w-bn 0.1  | 0.6662    | 0.083 |
| w-bn 0.3  | 0.6679    | 0    | w-bn 0.3  | 0.6679    | 0.0781|
| w-bn 0.5  | 0.6691    | 0.0025| w-bn 0.5  | 0.6691    | 0.1031|
| w-bn 0.7  | 0.6699    | 0.0033| w-bn 0.7  | 0.6699    | 0.1419|
| w-bn 0.9  | 0.6709    | 0.0099| w-bn 0.9  | 0.6709    | 0.1768|
| w-loss 0.1 | 0.6695    | 0.0349| w-loss 0.1 | 0.6695    | 0.0944|
| w-loss 0.3 | 0.6704    | 0.0191| w-loss 0.3 | 0.6704    | 0.0875|
| w-loss 0.5 | 0.6705    | 0.0179| w-loss 0.5 | 0.6705    | 0.1037|
| w-loss 0.7 | 0.6707    | 0.0204| w-loss 0.7 | 0.6707    | 0.1223|
| w-loss 0.9 | 0.6709    | 0.0331| w-loss 0.9 | 0.6709    | 0.1591|
| w-os 0.1  | 0.6687    | 0    | w-os 0.1  | 0.6687    | 0.657 |
| w-os 0.3  | 0.6692    | 0    | w-os 0.3  | 0.6692    | 0.668 |
| w-os 0.5  | 0.6695    | 0    | w-os 0.5  | 0.6695    | 0.699 |
| w-os 0.7  | 0.6699    | 0.0048| w-os 0.7  | 0.6699    | 0.2122|
| w-os 0.9  | 0.67     | 0.0314| w-os 0.9  | 0.67     | 0.2368|
| w-dbr 0.1 | 0.6663    | 0.0476| w-dbr 0.1 | 0.6663    | 0.0277|
| w-dbr 0.3 | 0.668    | 0.0654| w-dbr 0.3 | 0.668    | 0.1019|
| w-dbr 0.5 | 0.6688    | 0.0642| w-dbr 0.5 | 0.6688    | 0.2284|
| w-dbr 0.7 | 0.6692    | 0.0688| w-dbr 0.7 | 0.6692    | 0.3267|
| w-dbr 0.9 | 0.66940.077| 0.6696| w-dbr 0.9 | 0.66940.077| 0.3926|
Table 11. **Results on CIFAR-10 and ResNet-18 on two pairs**

| model     | acc         | conf    |
|-----------|-------------|---------|
| orig      | 0.8747      | 0.067   |
| orig-ft   | 0.8772      | 0.0698  |
| w-aug 0.1 | 0.8307      | 0.0683  |
| w-aug 0.3 | 0.8656      | 0.0648  |
| w-aug 0.5 | 0.8713      | 0.071   |
| w-aug 0.7 | 0.8769      | 0.0668  |
| w-aug 0.9 | 0.8783      | 0.0683  |
| w-bn 0.1  | 0.7839      | 0.03    |
| w-bn 0.3  | 0.8182      | 0.041   |
| w-bn 0.5  | 0.8466      | 0.0498  |
| w-bn 0.7  | 0.8654      | 0.0605  |
| w-bn 0.9  | 0.8765      | 0.0663  |
| w-loss 0.1| 0.5628      | 0.185   |
| w-loss 0.3| 0.7045      | 0.1402  |
| w-loss 0.5| 0.8144      | 0.093   |
| w-loss 0.7| 0.8591      | 0.0735  |
| w-loss 0.9| 0.8739      | 0.0698  |
| w-os 0.001| 0.7788      | 0.02125 |
| w-os 0.01 | 0.8289      | 0.037   |
| w-os 0.1  | 0.8638      | 0.05275 |
| w-os 0.3  | 0.8722      | 0.05975 |
| w-os 0.5  | 0.8735      | 0.06275 |
| w-os 0.7  | 0.8743      | 0.065   |
| w-os 0.9  | 0.8767      | 0.066   |
| w-dbr 0.1 | 0.7727      | 0.0728  |
| w-dbr 0.3 | 0.8498      | 0.0602  |
| w-dbr 0.5 | 0.8672      | 0.0592  |
| w-dbr 0.7 | 0.8739      | 0.0633  |
| w-dbr 0.9 | 0.8775      | 0.0622  |

Table 12. **Results on COCO and ResNet-50 on two pairs**

| model     | acc         | conf    |
|-----------|-------------|---------|
| orig      | 0.6604      | 0.2013  |
| orig-ft   | 0.6613      | 0.2298  |
| w-aug 0.1 | 0.6521      | 0.2937  |
| w-aug 0.3 | 0.6564      | 0.2628  |
| w-aug 0.5 | 0.6586      | 0.2697  |
| w-aug 0.7 | 0.66       | 0.2484  |
| w-aug 0.9 | 0.6607      | 0.2141  |
| w-bn 0.1  | 0.6548      | 0.0593  |
| w-bn 0.3  | 0.6572      | 0.0835  |
| w-bn 0.5  | 0.6593      | 0.0961  |
| w-bn 0.7  | 0.6607      | 0.1249  |
| w-bn 0.9  | 0.6614      | 0.175   |
| w-loss 0.1| 0.6605      | 0.0388  |
| w-loss 0.3| 0.6605      | 0.0442  |
| w-loss 0.5| 0.6608      | 0.0512  |
| w-loss 0.7| 0.6611      | 0.0605  |
| w-loss 0.9| 0.6616      | 0.1189  |
| w-os 0.1  | 0.6477      | 0.0     |
| w-os 0.3  | 0.6531      | 0.0     |
| w-os 0.5  | 0.6575      | 0.0     |
| w-os 0.7  | 0.6595      | 0.0968  |
| w-os 0.9  | 0.6602      | 0.1725  |
| w-dbr 0.1 | 0.6552      | 0.2957  |
| w-dbr 0.3 | 0.6571      | 0.2019  |
| w-dbr 0.5 | 0.6578      | 0.1828  |
| w-dbr 0.7 | 0.6583      | 0.1624  |
| w-dbr 0.9 | 0.6584      | 0.1607  |