Feature Weaken: Vicinal Data Augmentation for Classification

Songhao Jiang$^{1,3}$ Yan Chu$^2$* Tianxing Ma$^{1,3}$ Tianning Zang$^{1,3}$†

$^1$Institute of Information Engineering, Chinese Academy of Sciences
$^2$Harbin Engineering University
$^3$School of Cyber Security, University of Chinese Academy of Sciences

jiangsonghao@iie.ac.cn chuyan@hrbeu.edu.cn matianxing2000@163.com zangtianning@iie.ac.cn

Abstract

Deep learning usually relies on training large-scale data samples to achieve better performance. However, over-fitting based on training data always remains a problem. Scholars have proposed various strategies, such as feature dropping and feature mixing, to improve the generalization continuously. For the same purpose, we subversively propose a novel training method, Feature Weaken, which can be regarded as a data augmentation method. Feature Weaken constructs the vicinal data distribution with the same cosine similarity for model training by weakening features of the original samples. In especially, Feature Weaken changes the spatial distribution of samples, adjusts sample boundaries, and reduces the gradient optimization value of back-propagation. This work can not only improve the classification performance and generalization of the model, but also stabilize the model training and accelerate the model convergence. We conduct extensive experiments on classical deep convolution neural models with five common image classification datasets and the Bert model with four common text classification datasets. Compared with the classical models or the generalization improvement methods, such as Dropout, Mixup, Cutout, and CutMix, Feature Weaken shows good compatibility and performance. We also use adversarial samples to perform the robustness experiments, and the results show that Feature Weaken is effective in improving the robustness of the model.

1 Introduction

The advantages of deep learning usually have a linear relationship with model parameters and the scale of training samples. Large-parameter models and large-scale training samples have become a trend in deep learning model research (Bommasani et al. 2021). For example, GPT-3 has 175 billion parameters and is trained on broad data at scale (Brown et al. 2020). Deep learning models usually adopt the training method for minimizing the risk of the experience distribution of training samples, which is called the empirical risk minimization (ERM) principle (Vapnik 1998). In ERM mode, more training is conducted via memorization of data by model. However, a typical problem of this method is poor generalization, which can easily lead to over-fitting. And it often fails to achieve the same good performance as

*Corresponding Author
†Corresponding Author

Figure 1: Overview of the results of Mixup, Cutout, CutMix, and Feature Weaken on example images.
tics of different data and transform the original distribution of
samples, such as flipping and distorting changes in images
or easy data augmentation methods (EDA) in texts [Wei and
Zou 2019] [Guo, Han, and Huang 2021]. Feature mixing is
another kind of data augmentation, which can realize vic-
inal changes of samples independent of the characteristics
of samples, such as Mixup [Zhang et al. 2017] and CutMix
(Yun et al. 2019).

In this paper, we consider improving generalization. Un-
like previous methods of feature dropping and feature mix-
ing, we propose a novel training method of vicinal risk min-
imization, Feature Weaken, which also realizes the vicinal
distribution change of samples independently of the samples
characteristics and expert knowledge. Feature Weaken can
also be regarded as a data augmentation method. It mainly
reduces and weakens the vectors in the embedding-level or
hidden-level to transform the spatial distribution of the orig-
inal samples without changing the spatial angle of the sam-
ple in the same coordinate system. When applying Fea-
ture Weaken on the embedding-level, a representative com-
parison of our method with Mixup, CutMix, and Cutout is
shown in Figure 1. Feature Weaken can also coexist with
other data augmentation methods. When Feature Weaken
combines with Mixup or CutMix, it can better come into
the vicinal changes of samples as well as realize feature fusion
learning among samples.

We verify the effectiveness of Feature Weaken through
extensive experiments. In image classification, we use clas-
sical models such as ResNet [He et al. 2016] and DenseNet
[Huang et al. 2017]. We conduct experiments in MNIST
(Lecun et al. 1998), Fashion-MNIST (Xiao, Rasul, and Voll-
grad 2017), STL-10 (Coates, Ng, and Lee 2011), CIFAR-10,
and CIFAR-100 (Krizhevsky and Hinton 2009) image clas-
sification datasets. Compared with Mixup, Dropout, Cutout,
CutMix, and other methods, Feature Weaken achieves an ab-
so lutely leading performance. In text classification, we use
Bert [Devlin et al. 2019] as the backbone model. Compared
with advanced text data augmentation methods SenMixup
(Guo, Mao, and Zhang 2019b), TMix [Chen, Yang, and
Yang 2020] and SSMIX [Yoon, Kim, and Park 2021] in SST
(Socher et al. 2013), and TREC [Li and Roth 2002] datasets,
it exhibits a top performance. In addition, FGSM and I-
FGSM [Goodfellow, Shlens, and Szegedy 2014] are used to
generate adversarial samples, and the results show that Fea-
ture Weaken can improve the robustness of the model.

2 Related Work

Feature Drop: Feature Drop is a common regularization
strategy. According to the different positions of feature drop-
ning, it can be roughly divided into two categories. One is
the feature dropping of the hidden-level to achieve the neu-
rion to focus on the general features rather than the part of
features. Dropout [Hinton et al. 2012] [Srivastava et al. 2014],
DropBlock [Ghiasi, Lin, and Le 2018] and other variants [Ba
and Frey 2013; Wan et al. 2013; Park and Kwak 2016; Kes-
shari, Singh, and Vatsa 2019; Choe and Shim 2019; Pham
and Le 2021] selected the feature elements, feature regions,
channels, neurons, neural network paths of the hidden layer
to drop during the model training process to achieve a bet-
ter model generalization performance. Another is the feature
dropping of original samples to augment the sample data and
improve the generalization of the model. Cutout [ DeVries
and Taylor 2017], Random Erasing [Zhong et al. 2020],
HaS [Singh et al. 2018], and other methods [Chen et al. 2020;
Gong et al. 2021] can achieve the dropping of original sam-
ple features by randomly blocking or inserting noise. Neve-
theless, these methods may cause significant sample areas to
be removed, leading to insufficient features for deep learn-
ing models. Therefore, the feature dropping method affects
the learning effect of the model and weakens the joint effect
of network nodes and features. Unlike Feature Drop, Fea-
ture Weaken preserves the global features to ensure that
the original information is not lost.

Feature Mix: Feature Mix is another regularization
method that has been paid attention to by scholars in recent
years. It mainly achieves sample data augmentation through
different levels of feature mixing to improve the general-
ization of the model. Applying data augmentation technol-
ogy can overcome over-fitting and improve generalization
effectively. For example, in NLP, some scholars have aug-
mented the text data through synonym replacement, random
swap, random insertion, and random deletion to improve the
model generalization [Wei and Zou 2019] [Guo, Han, and
Huang 2021]. However, these methods require more expert
knowledge for guidance. Mixup and its variants realized the
training method beyond empirical risk minimization, and
utilized linear interpolation theory to synthesize data and la-
bel s [Zhang et al. 2017] [Guo, Mao, and Zhang 2019b] [Verma
et al. 2019] [Guo 2020] [Sawhney et al. 2022]. CutMix and its
variants used samples of other categories to replace original
regions [Yun et al. 2019] [Pamarzzi et al. 2022] [Walahalkar
et al. 2020] [Kim, Choo, and Song 2020] [Chen et al. 2022].
Moreover, due to the discreetness of text features, text mix-
ing augmentation methods mostly occurred in the represen-
tative layer and hidden layer [Guo, Mao, and Zhang 2019b]
[Chen, Yang, and Yang 2020]. While, SSMIX [Yoon, Kim,
and Park 2021], TreeMix [Zhang, Yang, and Yang 2022] and
other methods [Shi, Livescu, and Gimpel 2021] [Kim et al.
2022] realized the mixing of input-level samples by using
text structure. Although the feature mixing was proved to be a
VR M pattern beyond ERM [Zhang et al. 2017], Feature
Weaken uses weakening operation to transform the vicinal
distribution of the original samples, which is completely dif-
ferent from feature mixing or other data augmentation meth-
ods. As well as our method adjusts the intensity of feature
space, does not need huge computing costs, and can be used
in combination with other methods.

Other regularization methods: To improve the gener-
alization of deep learning algorithms, other regularization
methods were proposed. Normalization methods used stand-
dard deviations and variances to uniformly expand or shrink
a certain range of training samples or model weights [Ioffe
and Szegedy 2015] [Wu and He 2018] [Ba, Kiros, and Hint-
on 2016]. These methods concentrated the weight repre-
sentation in a certain range and made the optimization land-
scape significantly smoother [Santurkar et al. 2018] [Bjorck
et al. 2018].
et al. [2018]. As a result, the model generalization and training speed were improved. In addition, many scholars also studied other training techniques to improve model generalization, such as classical regularization, label smoothing, weight decay, and early stopping [Nowlan and Hinton [1992], Szegedy et al. [2016], Zhang et al. [2021], Müller, Kornblith, and Hinton [2019], Lienen and Hültermeier [2021], Guo et al. [2021], Loeschholz and Hutter [2017], Zhang et al. [2018], Krogh and Hertz [1991], Bai et al. [2021], Heckel and Yilmaz [2020]]. These methods usually improve the generalization of the model by increasing the training difficulty or limiting the training loss. Although Feature Weaken also affects gradient optimization in model training, these methods do not change the features of samples. As well as, these methods did not get rid of the training pattern of ERM.

3 Methodology

3.1 Feature Weaken

As shown in Figure 2, we put forward two methods, one is embedding-level Feature Weaken (FW-el), and the other is hidden-level Feature Weaken (FW-hl). In the embedding-level Feature Weaken mode, we use \( X \in \mathbb{R}^{W \times H \times C} \) to represent the original training image/sample, and \( Y \) to represent the label of the image/sample. Feature Weaken is used to generate a vicinal distribution sample \((\hat{X}, \hat{Y})\) of \((X, Y)\) by weakening the feature. We define the combining operation as:

\[
\hat{X} = (1 - Ws) \cdot X, \hat{Y} = Y.
\]

Where \( Ws \in (0, 1) \) represents the parameter of Feature Weaken and refers to the weaken strength of \( X \). The cosine similarity of \( X \) and \( \hat{X} \) remains the same and does not affect the label of the sample. Therefore, we assign the value of \( Y \) to \( \hat{Y} \). The new samples \( \hat{X} \) and the label \( \hat{Y} \) are used for model training with the original loss function.

For hidden-level Feature Weaken, we consider weakening the representation features of samples before the decision layer. Because the representation tensors are extracted by the deep model, and the representation tensors of samples are closer to the decision function. We think it is more conducive to model training. Therefore, for the representation features to weaken, the representation change of \((X, Y)\) as defined in the following equation:

\[
\hat{R}(X) = (1 - Ws) \cdot R(X), \hat{Y} = Y.
\]

Where \( R(\cdot) \) indicates the sample tensors extracted by the deep model, and \( Ws \) indicates the weaken strength. The \((\hat{R}(X), \hat{Y})\) is the weaken data of \((R(X), Y)\).

3.2 The Change of The Loss Optimization

For supervised training, we need to consider that the function \( f \) of a model can adequately describe the relationship between sample \( X \) and label \( Y \) in the distribution \( P(X, Y) \). According to ERM [Vapnik 1998], it is generally considered that the known distribution of the training data set \( D \) is regarded as an empirical distribution approximately equivalent to \( P \). The training function of a common ERM is shown as follows:

\[
E_{(X,Y) \sim P_D} = \frac{1}{n} \sum_i^n \text{loss}(f(x_i), y_i). \tag{3}
\]

The model is trained by minimizing risk \( E \). For Feature Weaken, we try to use the vicinal distribution \( P_{FW}(\hat{X}, \hat{Y} | X, Y) \) of weakened samples \((\hat{X}, \hat{Y} | X, Y)\), replacing the original empirical distribution \( P_D(X, Y) \), to augment the training sample data and improve the generalization ability. Therefore, Feature Weaken can be seen as a data augmentation method. The training function of Feature Weaken is changed as follows:

\[
E_{(X, \hat{Y}) \sim P_{FW}} = \frac{1}{n} \sum_i^n \text{loss}(f(\hat{x}_i), \hat{y}_i) \tag{4}
\]

\[
= \frac{1}{n} \sum_i^n \text{loss}(f((1 - Ws) \cdot x_i), y_i). \tag{5}
\]

So, when the method of gradient descent is used for parameter optimization of back-propagation, the gradient value \( \nabla \) of the vicinal sample \((\hat{X}, \hat{Y})\) changes as follows:

\[
\nabla = \frac{\partial \text{loss}}{\partial \theta} = \text{loss}'(f_\theta(\hat{X}), \hat{Y}) \cdot f'_\theta(\hat{X}), \tag{6}
\]

\[
f'_\theta(\hat{X}) = \hat{X}, \tag{7}
\]

\[
\nabla = \text{loss}' \cdot \hat{X} = (1 - Ws) \cdot \text{loss}' \cdot X. \tag{8}
\]

Compared with the gradient of loss function of the original sample, the gradient value is reduced due to the \( Ws \) of Feature Weaken. We can also regard this change as a decay of the training gradient, which has a similar effect to the learning rate or weight decay commonly seen in SGD training. Therefore, Feature Weaken can improve the model generalization by changing the gradient value of loss optimization.
However, Feature Weaken is gradient decay derived from augmented training data, unlike the learning rate or weight decay, which just changes the updated gradient.

### 3.3 The Change of Space Vector

Feature Weaken does not change the feature dimension or representation space of the original sample, but moves and weakens the original sample vector or representation tensor towards the coordinate axis origin in the same feature space. As shown in Figure 3, the original sample features and weakened features are mapped to a 3-dimensional coordinate system. In the same dimensional space, the original samples are relatively scattered. The boundary spacing of original samples is wider and easier to train. Feature Weaken makes the features more compact and makes it harder to distinguish between the boundary of the model training.

In addition, the angle between the space vector of the weakened samples with the coordinate axis remains the same as the original samples. We calculate it based on cosine similarity $\cosine(X, (1 - Ws) \cdot X)$, and cosine similarity is 1. Feature Weaken can be regarded as moving along the vector axis, that formed by the center of the original sample and the coordinates axis origin, towards the origin of the coordinates. The weakened sample vectors do not change the spatial angle of the original sample vectors. And the boundary spacing of the sample distribution is simultaneously scaled down. In model training, since the cosine similarity of the two space vectors is consistent, the segmentation boundary learned by the model can realize the segmentation of weakened samples and original samples. Therefore, Feature Weaken can obtain the vicinal distribution, and the vicinal risk minimization training can be well applied to the classification decision of original samples.

### 4 Experiments

In this section, we evaluate Feature Weaken for its capability to improve the performance and generalization of models on multiple tasks. We first study the effect of Feature Weaken on image classification (Section 4.1) and text classification (Section 4.2). Next, we show that Feature Weaken can improve the model robustness (Section 4.3). We analyze the influence of Feature Weaken parameters in Section 4.4. All experiments run on multiple NVIDIA TITAN XP GPUs with PyTorch.

#### 4.1 Image Classification Experiments

**Image datasets:** In image classification experiments, we use five common datasets and utilize the torchvision.datasets tool to download and call. They are as follows:

- **MNIST** (LeCun et al. 1998) consists of pictures of handwritten numerals, of which there are 10 categories corresponding to the Arabic numerals 0 to 9. Among them, there are 60,000 images in the training set and 10,000 images in the test set.
- **Fashion-MNIST** (Xiao, Rasul, and Vollgraf 2017) is no longer an abstract symbol but a more concrete human clothing. There are 10 categories: T-shirt/top, Trouser, Pullover, Dress, Coat, Sandal, Shirt, Sneaker, Bag, and Ankle boot. It also has 60,000 images in the training set and 10,000 images in the test set.
- **STL-10** (Coates, Ng, and Lee 2011) consists of 113,000 colour images, but it is composed of 100,000 unlabeled images. For labeled images, the training set contains 5,000 images, while the test set consists of 8,000 images. All training and test set images belong to 10 categories, such as cat, dog, or plane. STL-10 is mainly used for testing semi-supervised learning algorithms. To observe Feature Weaken performs when applied to fewer data of higher resolution images, we only use the labeled training set.
- **CIFAR-10** and **CIFAR-100** are the CIFAR datasets (Krizhevsky and Hinton 2009) and contain 60,000 colour images. CIFAR-10 has 10 distinct categories, such as frog, truck, or boat. CIFAR-100 contains 100 categories. Since some of the classes are visually very similar examples, CIFAR-100 requires a finer identification than CIFAR-10. Each dataset is split into a training set with 50,000 images and a test set with 10,000 images.

#### Table 1: Feature Weaken for various models.

| Model       | MNIST | Fashion-MNIST | STL-10 |
|-------------|-------|---------------|--------|
| ResNet-18   | 99.69 | 94.16         | 60.93  |
| + FW-hl     | 99.71 | 94.15         | 71.39  |
| ResNet-50   | 99.65 | 93.57         | 67.96  |
| + FW-hl     | 99.67 | 94.13         | 68.26  |
| ResNet-101  | 99.63 | 93.72         | 66.50  |
| + FW-hl     | 99.66 | 93.95         | 70.50  |
| DenseNet-121| 99.60 | 93.01         | 68.10  |
| + FW-hl     | 99.61 | 93.10         | 72.86  |

Feature Weaken for various models: We use ResNet-18, ResNet-50, ResNet-101 and DenseNet-121 for experiments.
Table 2: Comparison against other methods on MNIST, CIFAR, and STL-10. We show the positive and negative gains of the validation accuracy (%) of different methods compared with the baseline.

| Model | MNIST | CIFAR-10 | CIFAR-100 | STL-10 |
|-------|-------|----------|-----------|--------|
|       | Top-1 | Top-5 | Top-1 | Top-5 | Top-1 | Top-5 |
| ResNet-18 (baseline) | 99.66 | 88.76 | 99.53 | 63.27 | 86.5 | 60.93 | 96.4 |
| + Dropout (0.5) | +0.0 | +0.04 | -0.01 | +0.52 | +0.66 | +5.58 | +0.89 |
| + Mixup (α = 0.4) | +0.03 | +0.66 | -0.05 | -0.24 | -0.24 | +2.66 | -0.72 |
| + Cutout (PatchLength = 16) | +0.02 | +1.54 | +0.15 | +1.77 | +1.95 | +6.16 | +0.86 |
| + CutMix (α = 1.0) | -0.03 | +3.06 | +0.16 | +6.69 | +5.09 | +4.97 | +0.46 |
| + FW-hl (Ws = 0.8) | +0.02 | +1.24 | +0.17 | +2.70 | +2.29 | +11.46 | +1.50 |
| + Mixup (α = 0.4) + FW-hl (Ws = 0.8) | +0.03 | +1.47 | +0.16 | +3.62 | +2.79 | +11.01 | +2.10 |
| + Cutout (PatchLength = 16) + FW-hl (Ws = 0.8) | +0.06 | +2.40 | +0.21 | +4.49 | +3.76 | +13.17 | +1.83 |
| + CutMix (α = 1.0) + FW-hl (Ws = 0.8) | -0.02 | +3.55 | +0.24 | +6.95 | +5.46 | +14.17 | +1.73 |

Figure 4: The Top-1 (solid) and Top-5 (dashed) test accuracy plot of baseline (blue) and Feature Weaken (red) for CIFAR classification.

**Comparison against other methods:** We use ResNet-18 as the baseline model, and its parameter settings are consistent with the above settings. Experiments are conducted on MNIST, CIFAR-10, CIFAR-100, and STL-10. We report the mean optimal accuracy of 3 runs. The experimental parameters of CIFAR datasets are completely consistent with the above STL-10. The experimental data are evaluated by Top-1 accuracy and Top-5 accuracy. As shown in Table 2, we compare it with several methods, Dropout, Mixup, Cutout, CutMix, and Attentive CutMix. The Dropout parameter is set as 0.5, the α parameter of Mixup is set to 0.4, the α of CutMix is set to 1, and the Pathlength of Cutout is set as 16. These parameter settings have better performance according to the original papers. For Feature Weaken, we still choose the Feature Weaken (Ws = 0.8) on the hidden-level.

According to the experimental results, ResNet-18 combined with Feature Weaken achieves a good improvement. Compared with the baseline, the Top-1 accuracy of CIFAR-10 is improved by 1.24%, and the Top-5 accuracy is improved by 0.17%. For CIFAR-100, the increases are 2.70% and 2.29%, respectively. Although the experimental results do not exceed CutMix, Feature Weaken can be used with other methods simultaneously. Therefore, according to the experimental results, Feature Weaken can play a positive role in Mixup, CutMix, and Cutout. Especially when Feature Weaken is used with Mixup or CutMix, the advantages of spatial variation of Feature Weaken can be brought into play, and the model can also be encouraged to behave linearly in-between sample categories. When it is used with CutMix, the experimental performance is the best, and the Top-1 accuracy is 3.55%, 6.95%, and 14.17% higher than the baseline in CIFAR-10, CIFAR-100, STL-10.

**The Stability of Feature Weaken for CIFAR Classification:** To analyze the influence of Feature Weaken on model iteration, ResNet-18 is selected as the baseline model, two datasets of CIFAR-10 and CIFAR-100 are selected for evaluation, and their test sets are selected as validation sets. The plots of the accuracy of the validation sets with 200 epochs of CIFAR-10 and CIFAR-100 are constructed, as shown in Figure 4.

We can clearly find that when the ResNet-18 with Feature Weaken can not only significantly improve the model performance but also accelerate the convergence. In particular, with the decrease in learning rate at the 120th epoch, the baseline has obvious jitter and decreases the accuracy, but Feature Weaken is more stable.

**Feature Weaken with standard data augmentation:** Also, to evaluate the validity of Feature Weaken for models...
using standard data augmentation methods. Consistent with Cutout (DeVries and Taylor 2017), we used two augmentation methods, random crop and random horizontal flip, on the CIFAR-10 and CIFAR-100 datasets. We take ResNet-18 as the baseline, conduct experiments with Dropout (0.5) and Feature Weaken \((Ws = 0.8)\) respectively, and take the average of the highest accuracy of the 3 runs. The experimental results are shown in Table 3. It can be observed that using Feature Weaken can effectively improve the performance compared with baseline or Dropout. The Top-1 accuracy of CIFAR-10 and CIFAR-100 reached 94.44% and 76.05%, respectively.

### 4.2 Text Classification Experiments

**Text datasets:** As listed in Table 4, to evaluate the effect of Feature Weaken for text classification, we perform experiments on four text datasets, SST-1, SST-2, TRECCoarse, and TREC-fine. There are two 2-category datasets and three multi-category datasets. SST are classical sentiment classification datasets, while TREC datasets are sentence classification datasets.

**Comparison against other methods:** We use the Bert model as the backbone model. We use the bert-base-uncased pre-trained model from Huggingface Hub⁴ among all experiments. Experiments are initialized by seed 0~4 and calculate the average result of 5 runs. The Dropout parameter is 0.1, and the maximum length and the batch size of the input sequence are 128 and 32 on the all datasets. We use the AdamW optimizer with a learning rate of 2e-5, eps of 1e-8, weight decay of 1e-4, and epoch of 10. We select three excellent text mixing data augmentation methods: SenMixup (Zhang et al. 2017), Guo, Mao, and Zhang (2019a), TMix (Chen, Yang, and Yang 2020), and SSMIX (Yoon, Kim, and Park 2021) to be compared. TMix and SSMIX are the reproduction results of the predecessors’ work (Yoon, Kim, and Park 2021). We set \(α = 0.2\) for SenMixup and TMix. We set window size=10 for SSMIX. For TMix, we

\[ Ws = 0 \] respectively, and take the average of the highest accuracy of the 3 runs. The experimental results are shown in Table 3. It can be observed that using Feature Weaken can effectively improve the performance compared with baseline or Dropout. The Top-1 accuracy of CIFAR-10 and CIFAR-100 reached 94.44% and 76.05%, respectively.

### 4.3 Robustness Experiments

Model robustness is a research hotspot of deep learning models (Goodfellow, Shlens, and Szegedy 2014; Su et al. 2018; Zhang et al. 2019). Many scholars have proved that deep models are vulnerable to adversarial attacks caused by subtle perturbations (Goodfellow, Shlens, and Szegedy 2014). Furthermore, it has been established that the accuracy of the deep model is not related to the robustness of the model (Su et al. 2018; Zhang et al. 2019). Recently, many scholars have found that data augmentation methods, such as Mixup and CutMix, can well resist adversarial attacks and improve the robustness of models (Zhang et al. 2017; Yun et al. 2019; Rebuffi et al. 2021).

Considering that Feature Weaken can change the sample space vector and the classification boundary of the training samples, we believe Feature Weaken has a certain resistance to anti-attack. To evaluate the influence of Feature Weaken on the model robustness, we use FGSM \((ε = 0.1)\) and I-FGSM \((ε = 0.1, iter = 10)\) to add adversarial disturbances to the samples, to generate adversarial samples, and then conduct white-box and black-box tests. In the black-box test, FGSM and I-FGSM are first used to generate adversarial samples for ResNet-18, and then the adversarial samples are used to evaluate the results of other methods. The models used in the experiment are the trained models of CIFAR-10 in Section 4.1.

As shown in Table 6, we can observe that Feature Weaken can improve the model robustness and resist adversarial sample attacks in both black-box and white-box tests. Especially, when CutMix, Mixup, and Cutout are combined with Feature Weaken, they can also produce positive gains in model robustness of black-box, and Mixup with Feature Weaken has the highest robustness in the black-box test.

### 4.4 Ablation Studies

We perform ablation experiments on the CIFAR-10 dataset and evaluate a set of \(Ws\) parameters for FW-el and FW-hl.
| Model          | SST-1 | SST-2 | TREC-coarse | TREC-fine |
|---------------|-------|-------|-------------|-----------|
| Bert          | 54.37 | 91.82 | 97.08*      | 86.68*    |
| +Dropout (0.5)| 54.14 | 92.02 | 97.48       | 92.48     |
| +SenMixup     | 54.30 | 92.25 | 97.44       | 92.08     |
| +TMix         | 54.13 | 92.18 | 97.52*      | 90.16*    |
| +SSMIX        | 54.33 | 92.03 | 97.60*      | 90.24*    |
| +FW-el (Ws = 0.2) | 54.39 | 92.10 | 97.68       | 92.24     |
| +FW-el (Ws = 0.5) | 54.66 | 92.19 | 97.08       | 92.96     |
| +FW-hl (Ws = 0.8) | 53.99 | 92.20 | 97.60       | 87.64     |
| +FW-hl (Ws = 0.9) | 54.14 | 92.39 | 97.24       | 82.68     |

Table 5: Performance (accuracy(%)) of the model with Feature Weaken on text classification tasks. We report the mean accuracy of 5 runs, and the best results are highlighted in bold. We include results from (Yoon, Kim, and Park 2021)*.

| Model          | FGSM | I-FGSM |
|---------------|------|--------|
| ResNet-18     |      |        |
| + Feature Weaken |      |        |
| + Mixup       |      |        |
| + Feature Weaken + Mixup | 27.20 | 56.57  |
| + Cutout      |      |        |
| + Feature Weaken + Cutout | 37.46 | 49.47  |
| + CutMix      |      |        |
| + Feature Weaken + CutMix | 42.51 | 52.39  |

Table 6: The results (accuracy(%)) of Feature Weaken for adversarial samples. The best results (accuracy(%)) are highlighted in bold.

Figure 6: Feature Weaken on the embedding-level of the example images.

As shown in Figure 5 for hiddle-level, the Ws is approximately monotonically increasing between 0.1 and 0.9. With the increase of Ws, the accuracy is getting higher. While the embedding-level shows a monotonically decreasing effect with the increase of Ws. Overall, the effect of hidden-level Feature Weaken is generally better than embedding-level Feature Weaken. The optimal parameter is when Ws is 0.9 in hidden-level, the accuracy of the test set reaches 90.51%.

To observe the changes in weakened sample space, we perform an embedding-level Feature Weaken operation and show the weakened sample of different Ws. As shown in Figure 6 as the weaken strength increases, the color of the image has darkened and the texture becomes relatively blurry. When Ws is 0.99, the image is approximately black.

5 Conclusion

We propose a new regularization training method, Feature Weaken, which is different from the existing Feature Drop, Feature Mix, and other regularization methods. We consider the weakening of data features on the embedding-level and the hidden-level to generate the vicinal data distribution of the original samples. We then use the weakened features for model training. Feature Weaken can be regarded as a data augmentation method. Through experiments, we prove that Feature Weaken has good universality and can be used with other methods to produce significant improvement. And in the image or text classification task, compared with the feature mixing or feature dropping model, it has achieved a leading performance. We also analyze and discuss the function of Feature Weaken. On the one hand, Feature Weaken operation changes the process of loss optimization. Compared with the original method, its gradients are reduced during back-propagation, which is similar to the function of learning rate or weight decay, to increase the difficulty of model training. On the other hand, the spatial position of the original training sample changed by Feature Weaken does not change the spatial angle of the sample vector. Feature Weaken makes the classification boundaries of the samples...
more difficult to distinguish, and the training is more robust.
In the future, we will continue to study and explore the application scope of Feature Weaken, enrich its functions, and extend from global mode to local mode.

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