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Simple Summary: A good loss function should be flexible and adaptable to different activities and datasets. If the true class is not correctly recognized by the network (top1), it is likely to be placed in top5. In these cases, the neural network falsely recognizes a similar class with higher probability as the true class. In addition to true class, we proposed a loss function that accounts for false positive class. We call our proposed loss False Positive Loss (FPL). FPL is dynamic enough to be reformulated using other for user's tasks. False Positive Loss outperforms cross-entropy loss in 2D picture classification. We compared our loss with cross entropy on different models, datasets, and computer vision tasks. Results show that our loss works better in classification task, evaluating by metrics such as accuracy, and FP.

Abstract: When training deep neural networks tasks, the most popular choices are cross-entropy loss. On the other hand, in general speaking, a decent loss function can take on shapes that are considerably more flexible and ought to be adapted for different activities and datasets. In most of the classification tasks, generally if the true class is not correctly recognized by the network (top1), that class is placed among the five classes with the highest probability (top5). This shows that the network does not necessarily recognize the correct class with a low probability, but a class similar to it (such as 3 vs. 8 in mnist) assigns a higher probability and this causes a mistake in that task. Accordingly, we proposed a loss function deals with the error of class that the neural network incorrectly recognized as correct, in addition to the correct class error. We call our proposed loss as False Positive Loss (FPL), with the intention of viewing and designing loss functions not only through the utilization of true class but also through the utilization of the value of false positive classes. One of the core properties of our proposed loss is full adaptability, which makes False Positive Loss be fully capable of getting reformulated by using other widely used loss functions formulas based on the task or the need of the users. Extensive experimental results demonstrate that our suggested loss function outperforms other well-known losses on a variety of tasks and datasets. As can be observed, the performance of our False Positive Loss is superior to that of the cross-entropy loss when it comes to tasks involving 2D picture classification. We have compared our loss with cross entropy as the most common classification loss function on some models (such as ResNet-18, ResNet-50 and Efficientnet-V2) through classification known as a basic computer vision task. with both random or pre-trained initial weights. As a result, in some cases the models with our loss outperform the same tasks with cross entropy from the viewpoint of some metric (i.e. accuracy and FP). For example, the resnet-50 on cifar-10 dataset with random initialization indicated a top1 accuracy of 94.93 with cross entropy and 95.25 with our loss, while for top5 accuracy the results are 99.86 and 99.87, respectively.

Keywords: loss function; deep learning

1. Introduction

Optimizing neural networks hinges on the significance of loss functions. From a theoretical perspective, a loss function can be any differentiable function that transforms predictions and labels into a singular value. Nevertheless, given the extensive design scope, it's usually tricky to devise a potent loss function, and it's even more daunting to create a universal one that can function across diverse tasks and data sets. For instance, while L1/L2 losses are frequently employed for regression tasks, they are seldom applied in classification tasks. Focal loss and poly loss are frequently utilized to tackle the issue of overfitting of the cross-entropy loss in unevenly distributed object detection datasets [1], although their efficacy for this specific application hasn't been proven in this study.

Designing a universal loss Numerous recent publications have investigated new loss functions by means of meta-learning, ensembles of diverse losses, or compositing various types of losses [2–5]. As we motioned, many of the well-designed, well-known, and widely used loss functions are task specific for example in Face Net [6] researchers designed their own loss function to solve the face recognition task. This could be alluded to as a drawback. According to this fact designing a new loss function which could be applied to a variety of task is a work of art. Another issue in designing a loss function which is not getting serious attention from researchers who design loss function is value ignoring for false positive classes.

1.1. Investigation over image classification loss functions

Cross-entropy loss is utilized in models for perception tasks such as categorization, detection, and semantic segmentation [7–9]. These models are popular and state-of-the-art now. Several other losses have been suggested as potential ways to improve cross-entropy loss [1,10–12]. In contrast to other publications, the purpose of this one is to develop an adaptive framework for the purpose of methodically creating a classification loss function that is superior loss for class imbalance.

Triple loss[6] involves reducing the distance between an anchor and a positive, which share the same identity, while increasing the distance between the anchor and a negative with a different identity. We suggest a simple framework for the loss function.

1.2. Loss for class imbalance

Because of class imbalance, training detection models is a tough task. This is especially true for single-stage detectors. To solve the problem of class imbalance, numerous solutions such as "hard example mining" and "reweighing" have been created [13–17]. Focal loss is one of these ways, and it is aimed to reduce the class imbalance issue by focusing on the difficult samples. It is also used to train cutting-edge 2D and 3D detectors [1,18–21]. By utilizing the False Positive Loss (FPL) architecture, we were able to find an improved loss function that acts in a manner that is diametrically opposed to that of focused loss. In addition to this, we present an intuitive understanding of why it is vital to create multiple loss functions utilizing the FPL framework and tailoring them to different unbalanced datasets.

1.3. Robust loss to label noise

Another path that could be pursued in research is the development of loss functions that are resistant to label noise [22–26]. The method of incorporating a noise-resistant loss function into cross-entropy loss, such as Mean Absolute Error (MAE), is one that is frequently utilized. MAE and cross-entropy loss are said to be unified by the Taylor cross entropy loss. The researchers showed that by eliminating higher-order polynomials, the truncated cross-entropy loss function more closely resembles MAE, which is better equipped to handle label noise on datasets with synthetic label noise. In contrast, our False Positive Loss provides a broader framework for creating loss functions for different datasets by adjusting the hyperparameters of the loss functions.

1.4. loss functions that learn

The latest research reveals that the loss function can be trained concurrently during the learning process via gradient descent or meta-learning [2,3,5,27]. Notably, Taylor GLO employs CMA-ES to optimize a multivariate Taylor parameterization of both the loss function and learning rate schedule throughout the training [4,28]. The findings suggest that adopting a four-parameter parameterization leads to a trained loss function schedule that surpasses cross-entropy loss in classification tasks, a result attributed to the expansion of the search space with the polynomial order.

2. Materials and Methods

In this paper we have introduced a novel loss function, which cares the negative class(es) along with the positive class. The first key insight of our proposed loss, False Positive Loss, is to minimize the distance between one and the prediction probability of belonging of positive class, sum with, minimize the distance between zero and prediction probability of negative class(es). Moreover, we have designed a loss function which is fully adaptive based on the task and could be easily reformulate by other loss functions formulas. Furthermore, choosing the right hyperparameters in our proposed loss makes it overcome issues such as imbalanced data. We will dive into these details in the experimental results section.

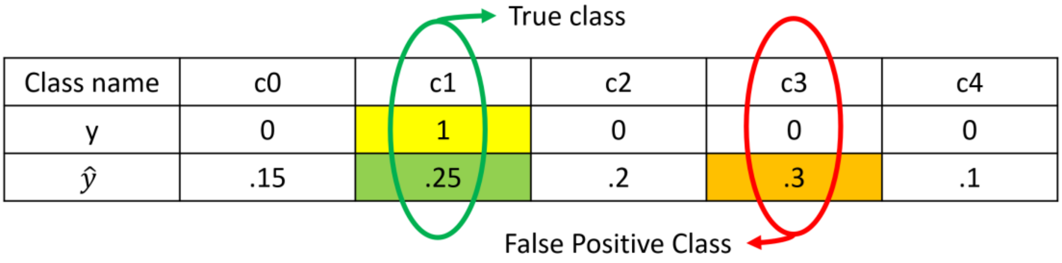
2.1. FPL definition

Based on the previous studies, to achieve more distance between classes, we have cared the positive distance and negative distance(s) simultaneously. For one sample, the positive one calculates the distance between the true class prediction and one. The negative one, on the other hand, computes the distance between the prediction of that negative class and zero, for each negative class. Our proposed loss is fully adaptive based on the need or desire of researchers. Our main goal in designing this loss was to ensure that the formulation of our proposed loss could be changed or integrated with all other well-known and widely used losses.

The general form of False Positive Loss is:

$$FPL\ (y, \hat{y}) = \ \alpha_T\ L_T(y, \hat{y}) + \alpha_F\ L_F(y, \hat{y}) \tag{1}$$

where T is true class, F is false positive class (see **Figure 1**), L_T is loss of true class, L_F is loss of false positive class, α_T and α_F are hyperparameters, y and $\hat{y}$ are target and predicted values, respectively. As it can be seen, our proposed loss general formula consists of 4 different terms. Here, the false positive class (F) is one of those classes that are not true class, with maximum prediction of model. For better understanding, **Figure 1** shows the false positive class for one sample that is predicted by model.



Class name	c0	c1	c2	c3	c4
y	0	1	0	0	0
$\hat{y}$	.15	.25	.2	.3	.1

True class
False Positive Class

Figure 1. The true class and false positive class when the model predicts one sample.

At first, L_T and L_F are cross entropy functions. In other words, they are defined as:

$$L_T\ (y, \hat{y}) = -\log(p_T) \tag{2}$$

where p_T is the prediction of true class, and

$$L_F\ (y, \hat{y}) = -\log(1 - p_F) \tag{3}$$

where p_F is the prediction of false positive class.

On the other hand, for α_T and α_F we have:

$$(\alpha_i = \frac{N-N_i}{N}) \tag{4}$$

where N is number of total samples and N_i is the number of samples in class i.

2.2. FPL and Class imbalance

Class imbalance is a serious challenge in tasks such as classification or object detection. For this purpose, we have used α_i coefficients to reduce the influence of the class that has more samples than others. This is especially noticeable in the background class of object detection methods. Although the authors of this article are aware that the growth of the cross-entropy function (logarithm) in the interval [0,1] is much faster than the linear growth of α (which makes the effect of α_i weaker against the cross-entropy), but finally with We achieved favorable results with these settings.

2.3. FPL Alternatives

We have considered multiple configurations for our proposed loss. Here we discuss some of these configurations:

$$L_T\,(y, \hat{y}) = (1 - \ p_T)^2 \tag{5}$$

and

$$L_F\,(y, \hat{y}) = (p_F)^2 \tag{6}$$

These two terms take a value based on a chosen loss. In other words, if we chose MSE for these terms, $L_T\,(y, \hat{y})$ would be the part of MSE which contains the value for true class and $L_F\,(y, \hat{y})$ would be the term in MSE formula which contains the value for false positive class respectively.

An alternative for α_i is as follows:

$$\alpha_i = (\frac{m - m_i}{m}) \tag{7}$$

where m is size of minibatch and m_i is number of samples with class i in that minibatch. The advantage of recent formula is that α_i is separately computed in each minibatch, which doesn't need to get subsidiary information to compute the loss.

An alternative for false positive class is using two or more classes with high probabilities that are not true class. So, the formula of FPL could be change to:

$$FPL\,(y, \hat{y}) = \ \alpha_T\, L_T(y, \hat{y}) + \sum_F \alpha_F\, L_F(y, \hat{y}) \tag{8}$$

where $F = \{F_1, F_2, .., F_k\}$ is set of k false classes with highest predictions.

3. Results

Here, we compare FPL with cross-entropy loss on the cifar10 classification task over various networks like ResNet18, ResNet50, and Efficientnet. For the following experiments, we used our implementation for the cifar10[29] classification task and also we optimize the hyperparameters in the mmclassification [30] open-source platform without any tuning.

3.1. Dataset

The Cifar10 dataset [29] was utilized to assess FPL. It comprises 50,000 training examples and 10,000 testing examples across 10 classes: Airplane, Automobile, Bird, Cat, Deer, Dog, Frog, Horse, Ship, and Truck. Some examples from this dataset are depicted in Figure 1.

3.2. Evaluation metrics

The performance of FPL is evaluated using the accuracy metric, which is calculated based on FP, FN, TP, and TF. We also investigated the loss performance using the number of FP that happened for classifying each class sample. Finally, we compare the purposed loss function against cross-entropy loss employing the number of FP and accuracy. Equation 9 demonstrates how accuracy is estimated based on the abovementioned quantitative metrics.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{9}$$

3.3. Hardware Setup

The hardware that is used and parameters in training of our implementation are indicated in Table 1.

Table 1. setup of configuration.

Hardware	Spec
GPU	NVIDIA® RTX A5000
CUDA version	v11.3 with cuDNN v8.2.0
Framework	PyTorch v1.9.1
Training parameters	Value
Batch size	64
Epochs	20
Initial Learning Rate	0.001
Optimizer	AdaDelta
Scheduler	CosineAnnealingLR

3.4. Evaluating FPL

Table 2 compares the results of False Positive Loss (FPL) with Cross Entropy (CE) as the most common classification loss function. FPL yields 39 and 5 lower False Positive predictions compared to Cross Entropy while using Efficientnet V2 and ResNet18 as the classifier backbone, respectively. Table 3 illustrates the results of training the resnet50 classifier using FPL and CE. FPL indicated better performance regarding 0.68 in Top-1 and 0.02 in Top-5 higher classification accuracy Compared to Cross Entropy.

Table 2. Comparing the performance of False Positive Loss with Cross Entropy. Our implementation determines the results.

Network	Loss	False Positive										Total
		Airplane	Automobile	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck	FP
Efficientnet V2	FPL	716	183	**375**	**500**	966	**116**	**461**	416	**45**	647	**4425**
	CE	**575**	183	495	899	**670**	167	494	**365**	63	**553**	4464
Resnet18	FPL	**402**	**131**	**260**	883	702	69	417	**281**	64	**322**	**3531**
	CE	411	144	359	**818**	**631**	**63**	**381**	315	**58**	356	3536

Table 3. Comparing the performance of the resnet50 classifier. MMCLASSIFICATION [30] repository used to train and test the method.

Network	Pretrained Dataset	FineTuned Dataset	Loss	Epochs	Top-1	Top-5
ResNet50	-	Cifar10 [29]	FPL	200	**95.25**	**99.87**
ResNet50	-	Cifar10 [29]	CE	200	94.93	99.85
ResNet50	ImageNet[31]	Cifar10 [29]	FPL	10	94.02	**99.93**
ResNet50	ImageNet[31]	Cifar10 [29]	CE	10	**94.22**	99.89

3.5. Analyzing Accuracy over epochs

Figure 2 shows the variation of the top-1 and top-5 accuracy over epochs (Eq. 1) during the training process for resnet50 using FPL and CE. FPL provides a smoother enlargement in accuracy during the training procedure, indicating the FPL potential that led the model weights to a better local optimum. On the other hand, cross-entropy could not suppress the second maximum value, which means that our proposed modification to cross-entropy can decrease False Positives.

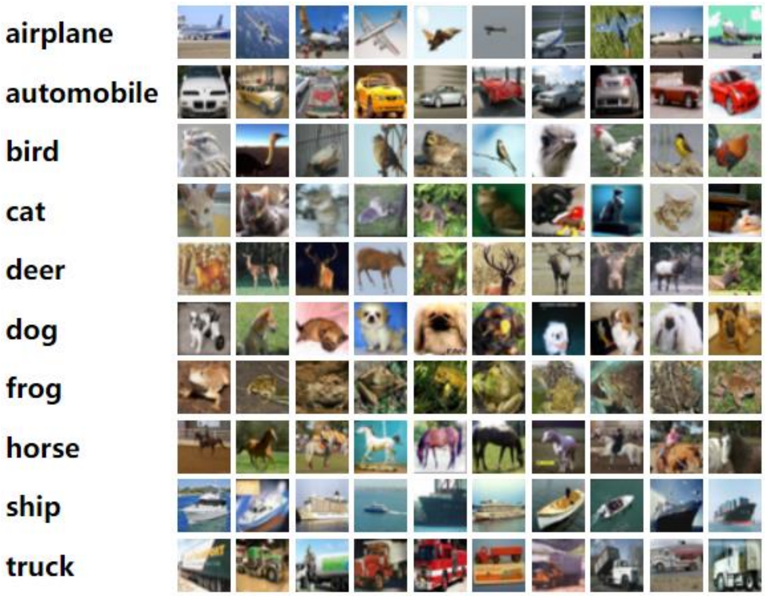


Figure 2. Cifar10 [29] is a Tiny Images dataset subset and consists of 60000 32x32 color RGB samples.

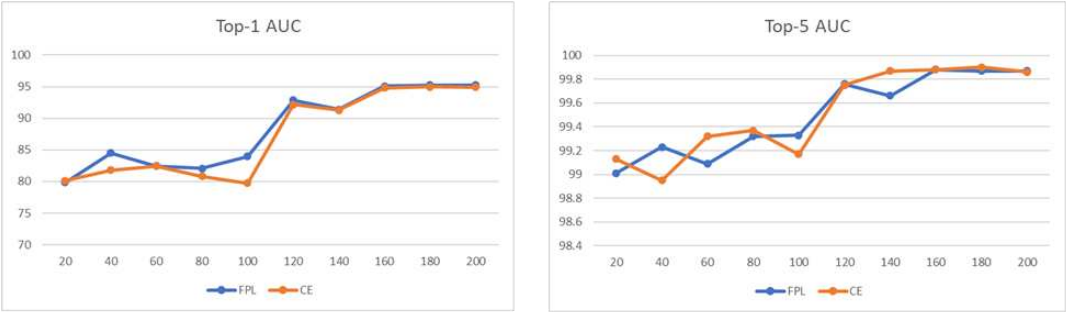


Figure 3. Top-1 and Top-5 accuracy over epochs.

4. Discussion

In different tasks based on different needs for researchers, the terms of FPL could take different values. In other words, it is totally up to the user. For instance, any well-known loss function such as MSE, CE, etc. can be used to find the corresponding value for each term of FPL. Therefore, our proposed loss function is fully adaptive.

False Positive Loss provides a framework for designing new loss functions, which have two main properties. First as we mentioned the general formula of this proposed loss function is fully adaptive consisting of 4 different parameters. α_i could take any value based on the need of research. L_T and L_F terms take value based on a chosen loss function such as widely used MSE. Secondly, it makes more distances between true class and false positive class by caring the importance of false positive class, which other loss functions do not allude to. For example, the cross-entropy loss does not care about the value of false positive classes, in the classification task, while out proposed loss function tries to increase the distance of true class and the maximum predicted wrong class. At this point, choosing the value for representing false positive classes is limited to the maximum predicted of false positive classes. However, it can be totally adaptive; i.e., we could use a mean or median over the value of false positive classes.

Although in all cases our loss is comparable with other ones, we had many results that we could not outperform other losses. We think tuning α_i or learning it during the training phase led to achieve better results.

5. Conclusions

Cross-entropy loss is popular for deep learning categorization. A good loss function should be flexible and adaptable to varied activities and datasets.

When a class is not accurately identified by the network (top1) in the majority of classification and object detection tasks, that class is often put among the top five classes with the highest likelihood (top5). This demonstrates that network assigned a similar class a greater probability than the true class, leading to an error in classification. in this paper, we presented a loss function in which, in addition to dealing with the true class error, the loss also deals with the class that is falsely identified as positive class.

One of the key characteristics of the loss we have proposed is adaptability, which enables False Positive Loss to be recast using other widely used loss function formulae depending on the job or need of the users. FPL performs better than well-known loss Cross-entropy loss in the classification of 2D images.

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