$C+1$ LOSS: LEARN TO CLASSIFY C CLASSES OF INTEREST AND THE BACKGROUND CLASS DIFFERENTIALLY

Anonymous authors
Paper under double-blind review

ABSTRACT

There is one kind of problem all around the classification area, where we want to classify $C+1$ classes of samples, including C semantically deterministic classes which we call Classes of Interest (CoIs) and the $(C+1)^{\text{th}}$ semantically undeterministic class which we call background class. In spite of most classification algorithm use softmax-based cross-entropy loss to supervise the classifier training process without differentiating the background class from the CoIs, it is unreasonable as each of the CoIs has its own inherent characteristics, but the background class dosen't. We figure out that the background class should be treated differently from the CoIs during training. Motivated by this, firstly we define the $C+1$ classification problem. Then, we propose three properties that a good $C+1$ classifier should have: separability, compactness and background margin. Based on them we define a uniform general $C+1$ loss, composed of three parts, driving the $C+1$ classifier to satisfy those properties. Finally, we instantialize a $C+1$ loss and experiment it in semantic segmentation, human parsing and object detection tasks. The proposed approach shows its superiority over the traditional cross-entropy loss.

1 INTRODUCTION

In machine learning, Softmax is one of the most widely used classifiers for classification, especially in CV tasks. During training, the Softmax classifier is often supervised by cross-entropy loss which treats each class without difference. However, there is a type of problem present all around the classification area, for which it is unreasonable to treat each class the same. We called this type of problem as $C+1$ classification. $C+1$ classification means classifying samples from C semantically deterministic classes and the $(C+1)^{\text{th}}$ semantically underterministic class. We can semantically uniquely define each of the C classes by its inherent characteristics, so we can say they are semantically deterministic. Generally, we are interested in the C classes, so we call them C CoIs and call one of them as a class of interest (CoI) hereafter. The $(C+1)^{\text{th}}$ class includes all the other stuff other than C classes. Because it doesn't have uniform inherent characteristics and we can't describe it uniquely in semantics. That is why we say it is semantically undeterministic. In most cases, we regard things belonging to the $(C+1)^{\text{th}}$ class as background, and we will call it background class hereinafter.

Based on the above description, we consider it is reasonable to treat the C CoIs and the background class differently during training. On one hand, for the C CoIs, it's reasonable to drive a $C+1$ classifier to learn a compact and independent representation space for each of them because of their respective inherent characteristics. Then the $C+1$ classifier can embed samples from each CoI into its own representation space. On the other hand, it's also reasonable to drive the $C+1$ classifier to map any samples from the background class into somewhere in feature space far away from all representation spaces of the C classes, considering samples from background class doesn't have any inherent characteristics from C CoIs. For example in figure 1, if we are interested in cat, we can recognize a cat from an image at the first glance by the knowledge in the subconscious which uniquely defines cat. On the contrary, we can also recognize a not-cat instantly because it doesn't have any inherent characteristics of cat.

Figure 1: $C+1$ classification cases(the source images are from ImageNet Russakovsky et al. (2015))

According to the internal characteristics of $C+1$ classification, we figure out that a $C+1$ classifier will be preferable if it has a compact and independent representation space for each of the C CoIs in addition to its separability for all classes. This can guarantee it behaves well while encountering a sample which have different styles from the samples of corresponding CoI in the training set. Furthermore, it will be much better if there is large enough margin between the background class and the C CoIs. This will make the classifier more robust and generalizable while encountering a sample from any new classes belonging to the super background class, especially those never appears in the training set. Above on these, we conclude three properties which a good $C+1$ classifier should have—**separability**, **compactness** and **background margin**. Based on the three properties, we define a uniform general $C+1$ loss which includes three parts corresponding to the three properties, driving the $C+1$ classifier to satisfy those properties. At last, we instantialize a $C+1$ loss and experiment it in semantic segmentation and object detection tasks, proving its superiority over the traditional cross-entropy loss. Because semantic segmentation and object detection are two of the most typical $C+1$ classification problems, and are widely used in AI systems.

Specifically, in semantic segmentation, Softmax is widely used for classifying each pixel of an image to one label of a predefined class set. Typically the predefined class set includes C CoIs and a background class. For instance, PASCAL VOC 2012 segmentation Everingham et al. (2010) contains 20 CoIs and a background class. The 20 CoIs are person, bird, cat, cow, dog, horse, sheep, aeroplane, bicycle, boat, bus, car, motorbike, train, bottle, chair, dining table, potted plant, sofa and tv/monitor. The background class contains all other stuff. In object detection, Softmax layer is usually used for classifying proposal boxes of an image to one of a predefined class set. For example, MS COCO Lin et al. (2014) contains 80 CoIs. A detector trained on it should classify all proposal boxes as one of the 80 CoIs or as background class. In these two typical tasks, the $C+1$ classifier needs to recognize all the CoIs, and classifies a variety of other things as background. This is difficult for cross-entropy loss to drive the classifier to learn well, which treats all samples indiscriminately during training.

This paper contains three contributions summarized as follows:

1.We define the $C+1$ classification problem present all around the classification area.

2.We propose three properties that a good $C+1$ classifier should have, and define a uniform abstract $C+1$ loss, which includes three parts corresponding to the three properties, driving the $C+1$ classifier to satisfy the three properties.

3.We instantialize a $C+1$ loss according to the properties, and experiment it on semantic segmentation and object detection task, proving its superiority over the popular cross-entropy loss.

2 Related work

2.1 Softmax

Softmax is one of the most widely used classifier for a variety of pattern recognition tasks. Nowadays there are a plenty of variants for Softmax, such as L2-Softmax Ranjan et al. (2017), Large-margin Softmax Liu et al. (2017), Angular Softmax Liu et al. (2016), Normface Wang et al. (2017),

AM-Softmax Wang et al. (2018a), CosFace Wang et al. (2018b) and ArcFace Deng et al. (2019). Large-margin Softmax is the first attempt to add parameter m into the original Softmax to control the margin and the larger m is, the larger the decision margin between the classes. Angular Softmax also known as SphereFace is an improvement to Large-margin Softmax with additional constraints on W and b, introducing the hypersphere manifold which makes the features suitable for open-set FR problem. L2-Softmax and Normface share similar ideas where L2-Softmax normalizes only the features and Normface normalizes both classifier weights and features and apply a scale parameter after that. The normalization and scaling steps push the learning progress focusing on optimizing angles among the classes, making the features not only separable but also discriminable. AM-Softmax(additive margin Softmax loss) and CosFace's works are inspired from SphereFace by moving the parameter m that controls the margin from angular space to cosine space by addition. This also makes the implementation easier. ArcFace(additive angular margin loss) moves the m parameter from scaling to addition to expand the optimization boundary. To sum up, they improve Softmax from these aspects: normalization of weights or features, margin in angular space or cosine space, setting of margin m. They use the parameter m in different ways resulting in different decision boundary. However, they treat all classes equally during training as Softmax. And we propose to give some special care for the background class. So Softmax and its variants are not the best choice for $C + 1$ classification problem.

2.2 Metric Learning

Metric learning aims to maximize inter-class variation and minimize the intra-class variation. Constrastive loss Chopra et al. (2005); Hadsell et al. (2006); Sun et al. (2014) drives the distance between a positive pair close to 0, and the distance between negative pair to fall within an absolute range. Triplet loss and its variants Weinberger & Saul (2009); Hoffer & Ailon (2015); Wang et al. (2014); Schroff et al. (2015); Ding et al. (2015); Cheng et al. (2016); Oh Song et al. (2016); Sohn (2016) drive the relative distances between positive pair and negative pair to fall lower than a preset threshold. Center loss Wen et al. (2016) drives model to learn a center for features of each class and penalizes the distances between features and their corresponding class center. Metric learning also treats each class equally, just from a metric perspective. They could not take care of the particularity of background class and the inherent characteristics of every semantic class. In addition, it's not appropriate to learn a center for background class because it has no semantically deterministic and unique definition.

2.3 Open-Set Recognition

Open-set recognition Bendale & Boult (2016); Ge et al. (2017); Shu et al. (2017); Neal et al. (2018); Liu et al. (2019); Yoshihashi et al. (2019); Oza & Patel (2019); Chen et al. (2019a); Qian et al. (2019); Yu & Tao (2019); Sun et al. (2020) is the one closest to our proposed $C + 1$ classification, wherein there are no training samples for the background class. However, the classifier needs to detect new classes while inferring. The $C + 1$ classification deals with another type of problem, wherein there are both training samples for C CoIs and the background class. In practice, it's impossible to contain all other semantic classes except the CoIs into the background class. Many samples of new semantic classes are likely yo be encounter and should be identified as background class while inferring. So we could call the $C + 1$ classification as semi-open-set recognition.

3 Method

3.1 Problem Definition

Firstly, we define some terminology as follows.

Semantic classes: a set of samples which could be described semantically uniquely and deterministically.

CoIs: a set of semantic classes that we are interested and need to be recognized.

Background classes: all other classes except CoIs, including those semantic classes we are not interested and all other stuff.

$C+1$ **Classification problem**: categorize each item of a set into one of the $C+1$ classes. Therein, $C+1$ classes comprise C CoIs and the $(C+1)^{\text{th}}$ class of not interested, also called background class. The C CoIs are semantically deterministic and unique. The background class is semantically underterministic and includes all stuff except those belonging to the C CoIs. The training set comprises many samples for each of the C CoIs and diverse samples from the background class. Being semantically deterministic means we can give a semantically deterministic and unique definition for each of the C CoIs according to its inherent characteristics. Being semantically underministic means the background class has no semantically deterministic and unique definition, because it lacks uniform inherent characteristics.

3.2 $C+1$ Loss

For each of the C CoIs, the C+1 classifier should grab the inherent characteristics, and differentiate the background class from them. In order to achieve this, we consider a $C+1$ classifier should satisfy the following three key properties.

1.**separability**: It should be able to separate all classes.

2.**Compactness**: The representation space of C CoIs should be compact enough.

3.**Background margin**: There should be large enough margin space which we call background margin between the background class and each of the C CoIs.

The property one guarantees a $C+1$ classifier has basic categorization ability for those samples that have similar distribution with the training set. But it can't ensure good generalizability for those that have distribution gap with training set. The property two makes sure that the classifier has good generalizability for those samples belonging to the C CoIs but with different distribution. And the property three gives the classifier good robustness and generalizability for those samples of the background class, especially some style of samples never present at the training set.

In order to drive a $C+1$ classifier to learn to satisfy the three key properties, we argue the $C+1$ loss should include at least three parts: $L_{separability}$, $L_{compact}$ and $L_{background}$, corresponding to the three properties respectively.

$$L_{C+1} = L_{separability} + \alpha L_{compact} + \beta L_{background} \tag{1}$$

Herein, $L_{separability}$ drives the classifier learn to discriminate all classes without difference, $L_{compact}$ drives the classifier to try to grab the inherent characteristics and to learn a compact representation space for each of the C CoIs, and $L_{background}$ drives the classifier to differentiate the background class from the C CoIs well.

In practice, we could adopt cross-entropy loss as an instantialized object for $L_{separability}$ and center loss Wen et al. (2016) for $L_{compact}$. As for $L_{background}$, we design a novel loss according to the property three as follows.

$$L_{background} = \operatorname{sign}\left(y_i = C+1\right) \frac{1}{N} \sum_i \frac{1}{C} \sum_{k=1} \left| m_b - d\left(\boldsymbol{f}\left(\boldsymbol{x}_i\right), \boldsymbol{c}_k\right) \right|_+ \tag{2}$$

Herein, $\operatorname{sign}(expression) = 1$ only when the $expression$ is true, otherwise 0. N is the number of background class sample. m_b is the background margin between background class and each of the C CoIs. x_i is a sample, and y_i is its class label index. c_k is the center of kth CoI. $f(x)$ is a mapping function for extracting feature of sample x. $f(x)$ followed by softmax layer composes the $C+1$ classifier. Without losing generality, $f(x)$ is a deep neural network.

As centers for center loss and the instantialized $L_{background}$, we define three types of center representation.

1.Represent each center of C CoIs as a learnable weight vector.

2.Represent each center of C CoIs as a moving average of sample features of the corresponding class.

3.Represent each center of C CoIs as the classifier weight vector of each class from the softmax layer.

Specifically the third center representation means that we share the center vector parameter with the softmax layer of the C CoIs, and ignore the weight vector of background. We define a center for every CoI, but not the background class. For every CoI, there are a bunch of inherent characteristics which can uniquely and deterministically define it semantically, however there are no unique and deterministic inherent characteristics for the background class. Despite all this, we still can calculate loss based on the centers of C CoIs for samples from both CoIs and the background class by adopting the above described instantialized $L_{compact}$ and $L_{background}$.

3.3 APPLICATION

The $C + 1$ classifier described in the previous section can be applied to many tasks, including semantic segmentation, object detection, human pose estimation and any other classification problem which include the background class. In semantic segmentation, we label each foreground pixel with a semantic label, and all other pixels with background label. In object detection, we classify the area of object of interest as one of the CoIs, such as pedestrian, car and so on, and all other areas as background. In human pose estimation, we label the position of each human keypoint with proper semantic label and the other position with the background label. As for other cases, if the recognition problem needs to recognize certain number of semantically deterministic classes and the other stuff, the $C + 1$ classifier can also apply to it. In this paper, we just use some CV tasks as the experimental field, because they are the most common tasks in AI system. Besides the application scenarios presented above, it can also be applied to many other tasks, such as attribute recognition, web text classification, speech recognition and so on.

3.4 DISCUSSIONS

We think $C + 1$ classifier is rational because it has sufficient prerequisites. For the semantically deterministic C CoIs, it's rational and reachable to embed each class into an independent hypersphere. Because every CoI has its own semantically deterministic definition, corresponding to a set of inherent characteristics. For example, the cat in the figure 1 has some type of fur, innate shape and contour. As for the background class, it has no semantically deterministic definition, so there are no definite and uniform features for it. Then it's not rational to embedding this class into an hypersphere. But it may be reasonable to map it to the outer space of all hyperspheres of the C CoIs. Because the C CoIs is separable from the background class which doesn't have deterministic inherent characteristics.

3.5 ANALYSIS

After training, if the classifier can embed all samples of the C CoIs into their own hypersphere, it's almost impossible to map a novel sample belonging to the background class into any hypersphere of the C CoIs even if the classifier has no any knowledge about the novel sample. Assume a novel sample belonging to the background class is new-brand and there are no similar type of samples present at the training set, then we can treat it as a random sample from the nature. From the perspective of statistics, the probability of recognizing it as the background class is close to 1. Formally, we assume the full d-dimension features representation space is a super ball with R_L as the radius, and the sample features of each CoI are distributed in a small super ball with R as the radius. Then the probability of mapping the random sample to the outer space of all the super balls of C CoIs is

$$p\left(x_{\text{random}}\right) = 1 - \frac{C \cdot R^d}{R_L^d} \tag{3}$$

Therein, $R \ll R_L$ is a reasonable assumption, C is a constant, and d is usually very large, such as hundreds, even thousands, then the $p\left(x_{\text{random}}\right)$ is close to 1.

Table 1: Effectiveness validation experiment on PASCAL VOC

Loss function	mIoU	mAcc	aAcc
$L_{separability}$	75.93	85.47	94.59
$L_{separability} + L_{compact}$	76.25	86.1	94.61
$L_{separability} + L_{compact} + L_{background}$	**77.35**	**86.37**	**94.58**

4 EXPERIMENT

We comprehensively evaluate the effectiveness of $C + 1$ classifier on semantic segmentation, and then transfer the solution to object detection with some minor adjustments. During inference we use the output of softmax layer for classification.

4.1 SETTINGS

Semantic segmentation. Semantic segmentation aims to label each pixel of an image with one semantic class label or background label. We evaluate our methods on two popular semantic segmentation dataset: PASCAL VOC and PASCAL Context and a human parsing dataset LIP. To make a fair comparison, for PASCAL VOC 2012 and PASCAL Context we adopt MMsegmentation Contributors (2020) as a unified framework for the experiments on semantic segmentation.

PASCAL VOC 2012 contains 20 foreground object classes and one background class. The original dataset contains 1,464 (train), 1,449 (val), and 1,456 (test) pixel-level annotated images. Following the settings in Chen et al. (2018b), we use the augmented dataset by the extra annotations provided by Everingham et al. (2015), which contains 10,582 (trainaug) training images. Following the setting in MMsegmmentation, we resize the images into 512×512 and the output stride is 8. We adopt "SGD" as the optimizer and "poly" policy as the learning rate schedule. In addition, we set the initial learning rate as 0.01 and weight decay as 0.0005. Furthermore, the batch size is 16 and the number of iterations is 20K. We evaluate the performance of our method and other methods using single scale and without flipping.

PASCAL Context Mottaghi et al. (2014) contains 459 labeled categories, including 10,103 images, of which 4,998 are used for training and 5,105 are used for validation. The most widely used setting is to use most frequent 59 categories as the semantic object classes and all the remaining categories as background. Following the setting in MMsegmmentation, we resize the images to 480×480. The initial learning rate is set to 0.004 and weight decay to 0.0001. The batch size is 16 and the number of iterations is 40K. We evaluate the performance using single scale and without flipping.

LIP Gong et al. (2017) is a human part segmentation dataset, with 50,462 images in total, including 30,462 images for training, 10,000 images for validation and 10,000 images for testing. In addition, it contains 19 semantic classes and 1 background class. We resize the images to 473×473. The initial learning rate is set to 0.0028 and weight decay to 0.0005. The batch size is 16 and the number of iterations is 110K. We evaluate the performance using single scale and flipping.

Table 2: Effect of three different center representations

Center representation	mIoU	mAcc	aAcc
Learnable	76.68	86.29	94.71
Moving average	**77.35**	**86.70**	**94.87**
Shared	76.99	86.57	94.79

4.2 SEMANTIC SEGMENTATION

4.2.1 ABLATION STUDY

For ablation study, we use VOC+Aug as the training set. All images are resized to 512x512 as input. Iteration number is 20K. The initial learning rate is 0.01, and then decayed by "poly" policy with

Table 3: Weights' effect of $L_{compact}$

Weights for $L_{compact}$	mIoU	mAcc	aAcc
0.01	76.82	86.43	94.63
0.1	**77.35**	**86.70**	**94.87**
1	75.22	85.25	94.39

Table 4: Weights' effect of $L_{background}$

Weights for $L_{background}$	mIoU	mAcc	aAcc
0.001	75.93	86.04	94.51
0.0001	**77.35**	**86.70**	**94.87**
0.00001	76.47	85.91	94.71

power being 0.9. Batch size is set to 16. We use the same setting for the all ablation study unless specified otherwise.

At first, we validate the effectiveness of $C + 1$ classifier on PASCAL VOC by DeeplabV3+ Chen et al. (2018a) with ResNet50 as backbone. As for the C CoIs, we use moving average of L_2-normalized features as centers. We set the weights of $L_{compact}$ and $L_{background}$ as 0.1 and 0.0001 respectively if each of them is used.

From the experiment performance on table 1, we observe that $L_{compact}$ and $L_{background}$ can both boost the performance significantly. When $L_{compact}$ is used with $L_{separability}$, we can improve mIoU by 0.32. If $L_{background}$ added, we can get positive improvement 1.10 furthermore, and $C + 1$ loss in total can improve the mIoU by 1.42. For semantic segmentation task, this is a significant improvement.

Then, we validate the effect of three different center representations on the performance. In this group experiments, we set the weighs of $L_{compact}$ and $L_{background}$ as 0.1 and 0.0001 respectively. We use the same hyper-parameters as above. From the experiment performance on table 2, we could find that moving average achieves the best performance.

Next we analyze the effect of weights of $L_{compact}$ and $L_{background}$. According to the above experiments, moving average is the best center representation, so we adopt moving average in this and following experiments. First, we observe the weights' effect of $L_{compact}$ while set the weight of $L_{background}$ as 0.0001. From table 3 we can observe that 0.1 is a reasonable weight for $L_{compact}$. Then we test the weight's effect of $L_{background}$ while set the weight of $L_{compact}$ as 0.1. From table 4 we find that 0.0001 is a reasonable weight for $L_{background}$. From experiment performance, we can conclude that setting the weights of $L_{compact}$ and $L_{background}$ as 0.1 and 0.0001 respectively is a proper choice.

Finally, we list the performance details of all classes on PASCAL VOC with and without $C + 1$ loss in table 5. We can observe our method get superior performance over baseline on 13 classes.

4.2.2 BACKBONE

To prove the generality of $C + 1$ classifier, we experiment on PASCAL VOC by DeepLabV3+ with ResNet101 as the backbone. Considering the larger capacity of ResNet101, we set the iteration as 40K and other hyper-parameters the same as with ResNet50 as the backbone.We can observe that $C + 1$ classifier is also better than the baseline. Moving average is used as the center representation. The weights of $L_{compact}$ and $L_{background}$ are set to 0.01 and 0.0001 respectively.

4.2.3 SEMANTIC SEGMENTATION ALGORITHM

To prove the generality of $C + 1$ classifier, we further experiment on PASCAL VOC by other SOTA semantic segmentation algorithms, i.e. HRNet Sun et al. (2019) and OCRNet Yuan et al. (2020). Both of them take HRNetW48 as backbone.We set the hyper-parameters the same as DeeplabV3+ with ResNet101 as the backbone, including center representation and iteration. For OCRNet+ours,

Table 5: The performance details of all classes on PASCAL VOC with and without $C + 1$ loss

Category	$L_{separability}$		L_{C+1}		Category	$L_{separability}$		L_{C+1}	
	mIoU	mAcc	mIoU	mAcc		mIoU	mAcc	mIoU	mAcc
aeroplane	90.13	96.01	92.03	95.38	diningtable	57.14	60.24	54.87	57.38
bicycle	41.75	91.74	41.56	95.38	dog	84.18	93.75	86.26	94.38
bird	86.62	92.32	87.71	94.17	horse	84.86	88.88	84.74	92.98
boat	70.92	87.90	72.43	87.27	motorbike	84.51	91.09	83.90	92.30
bottle	76.63	87.79	78.37	89.66	person	84.99	91.61	85.08	91.08
bus	94.68	97.49	95.05	96.99	pottedplant	60.82	70.29	59.70	70.70
car	86.40	93.06	86.03	93.85	sheep	83.93	92.37	88.47	91.98
cat	90.50	94.84	93.10	96.94	sofa	46.29	53.87	55.80	65.52
chair	36.36	55.11	37.44	54.77	train	90.21	94.10	89.40	93.97
cow	86.65	90.30	87.68	90.18	tv/monitor	62.69	75.31	70.45	80.79
background	94.21	97.33	94.35	97.32					

Table 6: Experiment results on PASCAL VOC by DeeplabV3+ with ResNet101 as the backbone

Loss	mIoU	mAcc	aAcc
DeepLabV3+	78.62	86.55	95.22
DeepLabV3++ours	**80.00**	**87.99**	**95.50**

we set the weights of $L_{compact}$ and $L_{background}$ are set to 0.1 and 0.0001 respectively, and HRNet+FCN+ours with 0.01 and 0.0001 respectively. Results in table 7 shows that our C+1 classifier is also applicable to other semantic segmentation algorithms. Especially on the OCRNet, our method can improve the baseline with 0.99 mIoU.

4.2.4 More experiments on other semantic segmentation datasets

To prove the generalization ability of our classifier to other scenarios, we also experiment DeeplabV3+ with ResNet50 as backbone on other semantic segmentation dataset, i.e. PASCAL Context. We use the moving average as the center representation. All images are resized to 480x480. Iteration number is 40K. Initial learning rate is set to 0.004. Batch size is set to 16. From table 8, we can observe our classifier can also improve the performance on PASCAL Context too.

4.3 Human Parsing

For LIP, all images are resized to 473x473. The initial learning rate and weight decay are set to 0.0028 and 0.0005 respectively. The batch size is 16 and the number of iterations is 110K. Experimental results are shown in Table 9.

There are also some other datasets, i.e. Cityscapes Cordts et al. (2016), KITTI Geiger et al. (2013) and ADE20K Zhou et al. (2017; 2019). However these datasets almost have no background pixel, so it cannot be defined as a $C + 1$ classification problem. Thus we don't experiment on them.

Table 7: Experiment results on different SOTA semantic segmentation algorithms

Method	mIoU	mAcc	aAcc
HRNet48+FCN	76.23	84.95	94.66
HRNet48+FCN+Ours	**76.96**	**85.38**	**94.81**
OCRNet	77.14	85.92	94.94
OCRNet+ours	**78.13**	**86.92**	**95.09**

Table 8: Experiment results on PASCAL Context

Method	mIoU	mAcc	aAcc
DeepLabV3+	47.34	57.40	74.18
DeepLabV3++ours	**47.81**	**58.29**	**74.68**

Table 9: Experiment results on LIP

Method	Flip-test	mIoU	mAcc	aAcc
HRNet	N	53.42	65.20	86.80
	Y	54.53	65.77	87.30
HRNet+ours	N	**53.76**	**65.63**	**86.81**
	Y	**54.78**	**66.19**	**87.32**

4.4 OBJECT DETECTION

Object detection. In this section, we migrated our approach to the object detection task.Nowadays, existing methods for object detection can be divided into anchor-based and anchor-free according to whether anchors are needed. Among them, the anchor-based methods are quite different from the segmentation task in the classification head. Specifically, semantic segmentation is the classification of pixels. The target to be classified corresponds to the feature map position one-by-one, while the anchor-based methods needs to classify the anchor boxes, which is multiple to the feature map position. Therefore, we choose to verify our approach on the FCOS Tian et al. (2019) model which is the most similar method in object detection to the FCN-based segmentation network.

To make a fair comparison, we adopted MMdetection Chen et al. (2019b) as a unified framework for all the experiments on object detection. We use COOC2017 as the evaluation dataset for object detection. COOC2017 contains 80 annotated targets, with 118K training images, 5K validation images and 20K testing images. The standard COO-style evaluation is adopted. To compare fairly, we use the public MMdetection platform with the provided training setup and learning rate schedule for 2x. The batch size is set as 16.

The experimental results in table 10 show that our method can improve the detection performance of small objects.

5 CONCLUSION

In this paper, firstly we define the $C+1$ classification problem. Then we propose a uniform abstract $C+1$ loss for training the $C+1$ classifier. Furthermore we design a instantialized $C+1$ loss and prove its superiority over popular cross-entropy loss on some CV tasks, including semantic segmentation and object detection. In the future, we will explore more instantialized object for the $C+1$ loss and experiment them on more problems, proving its generalizability on common $C+1$ classification.

Table 10: Experiment results on COCO

Method	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
FCOS(R50)	38.5	57.7	41.0	21.9	42.8	48.6
FCOS(R50)+ours	**39.0**	**58.5**	**41.6**	**23.1**	**43.0**	**49.5**
FCOS(X101-64x4d)	42.6	62.3	45.6	25.7	46.3	54.6
FCOS(X101-64x4d)+ours	**43.0**	**62.9**	**46.1**	**27.2**	**46.8**	**54.5**

REFERENCES

Abhijit Bendale and Terrance E Boult. Towards open set deep networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1563–1572, 2016.

Guangyi Chen, Tianren Zhang, Jiwen Lu, and Jie Zhou. Deep meta metric learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 9547–9556, 2019a.

Kai Chen, Jiaqi Wang, Jiangmiao Pang, Yuhang Cao, Yu Xiong, Xiaoxiao Li, Shuyang Sun, Wansen Feng, Ziwei Liu, Jiarui Xu, Zheng Zhang, Dazhi Cheng, Chenchen Zhu, Tianheng Cheng, Qijie Zhao, Buyu Li, Xin Lu, Rui Zhu, Yue Wu, Jifeng Dai, Jingdong Wang, Jianping Shi, Wanli Ouyang, Chen Change Loy, and Dahua Lin. MMDetection: Open mmlab detection toolbox and benchmark. *arXiv preprint arXiv:1906.07155*, 2019b.

L. C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In *European Conference on Computer Vision*, 2018a.

Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In *Proceedings of the European conference on computer vision (ECCV)*, pp. 801–818, 2018b.

De Cheng, Yihong Gong, Sanping Zhou, Jinjun Wang, and Nanning Zheng. Person re-identification by multi-channel parts-based cnn with improved triplet loss function. In *Proceedings of the iEEE conference on computer vision and pattern recognition*, pp. 1335–1344, 2016.

Sumit Chopra, Raia Hadsell, and Yann LeCun. Learning a similarity metric discriminatively, with application to face verification. In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, volume 1, pp. 539–546. IEEE, 2005.

MMSegmentation Contributors. MMSegmentation: Openmmlab semantic segmentation toolbox and benchmark. `https://github.com/open-mmlab/mmsegmentation`, 2020.

Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 3213–3223, 2016.

Jiankang Deng, Jia Guo, Niannan Xue, and Stefanos Zafeiriou. Arcface: Additive angular margin loss for deep face recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4690–4699, 2019.

Shengyong Ding, Liang Lin, Guangrun Wang, and Hongyang Chao. Deep feature learning with relative distance comparison for person re-identification. *Pattern Recognition*, 48(10):2993–3003, 2015.

M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The pascal visual object classes (voc) challenge. *International Journal of Computer Vision*, 88(2):303–338, June 2010.

Mark Everingham, SM Ali Eslami, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes challenge: A retrospective. *International journal of computer vision*, 111(1):98–136, 2015.

Zongyuan Ge, Sergey Demyanov, Zetao Chen, and Rahil Garnavi. Generative openmax for multi-class open set classification. In *British Machine Vision Conference 2017*. British Machine Vision Association and Society for Pattern Recognition, 2017.

Andreas Geiger, Philip Lenz, Christoph Stiller, and Raquel Urtasun. Vision meets robotics: The kitti dataset. *The International Journal of Robotics Research*, 32(11):1231–1237, 2013.

Ke Gong, Xiaodan Liang, Dongyu Zhang, Xiaohui Shen, and Liang Lin. Look into person: Self-supervised structure-sensitive learning and a new benchmark for human parsing. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 932–940, 2017.

Raia Hadsell, Sumit Chopra, and Yann LeCun. Dimensionality reduction by learning an invariant mapping. In *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, volume 2, pp. 1735–1742. IEEE, 2006.

Elad Hoffer and Nir Ailon. Deep metric learning using triplet network. In *International workshop on similarity-based pattern recognition*, pp. 84–92. Springer, 2015.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollar, and Larry Zitnick. Microsoft coco: Common objects in context. In *ECCV*. European Conference on Computer Vision, September 2014. URL https://www.microsoft.com/en-us/research/publication/microsoft-coco-common-objects-in-context/.

Weiyang Liu, Yandong Wen, Zhiding Yu, and Meng Yang. Large-margin softmax loss for convolutional neural networks. In *ICML*, volume 2, pp. 7, 2016.

Weiyang Liu, Yandong Wen, Zhiding Yu, Ming Li, Bhiksha Raj, and Le Song. Sphereface: Deep hypersphere embedding for face recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 212–220, 2017.

Ziwei Liu, Zhongqi Miao, Xiaohang Zhan, Jiayun Wang, Boqing Gong, and Stella X Yu. Large-scale long-tailed recognition in an open world. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2537–2546, 2019.

Roozbeh Mottaghi, Xianjie Chen, Xiaobai Liu, Nam-Gyu Cho, Seong-Whan Lee, Sanja Fidler, Raquel Urtasun, and Alan Yuille. The role of context for object detection and semantic segmentation in the wild. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 891–898, 2014.

Lawrence Neal, Matthew Olson, Xiaoli Fern, Weng-Keen Wong, and Fuxin Li. Open set learning with counterfactual images. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pp. 613–628, 2018.

Hyun Oh Song, Yu Xiang, Stefanie Jegelka, and Silvio Savarese. Deep metric learning via lifted structured feature embedding. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4004–4012, 2016.

Poojan Oza and Vishal M Patel. C2ae: Class conditioned auto-encoder for open-set recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2307–2316, 2019.

Qi Qian, Lei Shang, Baigui Sun, Juhua Hu, Hao Li, and Rong Jin. Softtriple loss: Deep metric learning without triplet sampling. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 6450–6458, 2019.

Rajeev Ranjan, Carlos D Castillo, and Rama Chellappa. L2-constrained softmax loss for discriminative face verification. *arXiv preprint arXiv:1703.09507*, 2017.

Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015. doi: 10.1007/s11263-015-0816-y.

Florian Schroff, Dmitry Kalenichenko, and James Philbin. Facenet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 815–823, 2015.

Lei Shu, Hu Xu, and Bing Liu. Doc: Deep open classification of text documents. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pp. 2911–2916, 2017.

Kihyuk Sohn. Improved deep metric learning with multi-class n-pair loss objective. In *Advances in neural information processing systems*, pp. 1857–1865, 2016.

Ke Sun, Bin Xiao, Dong Liu, and Jingdong Wang. Deep high-resolution representation learning for human pose estimation. In *CVPR 2019*, June 2019. URL https://www.microsoft.com/en-us/research/publication/deep-high-resolution-representation-learning-for-human-pose-estimation/.

Xin Sun, Zhenning Yang, Chi Zhang, Keck-Voon Ling, and Guohao Peng. Conditional gaussian distribution learning for open set recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 13480–13489, 2020.

Yi Sun, Yuheng Chen, Xiaogang Wang, and Xiaoou Tang. Deep learning face representation by joint identification-verification. In *Proceedings of the 27th International Conference on Neural Information Processing Systems-Volume 2*, pp. 1988–1996, 2014.

Zhi Tian, Chunhua Shen, Hao Chen, and Tong He. Fcos: Fully convolutional one-stage object detection. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 9627–9636, 2019.

Feng Wang, Xiang Xiang, Jian Cheng, and Alan Loddon Yuille. Normface: L2 hypersphere embedding for face verification. In *Proceedings of the 25th ACM international conference on Multimedia*, pp. 1041–1049, 2017.

Feng Wang, Jian Cheng, Weiyang Liu, and Haijun Liu. Additive margin softmax for face verification. *IEEE Signal Processing Letters*, 25(7):926–930, 2018a.

Hao Wang, Yitong Wang, Zheng Zhou, Xing Ji, Dihong Gong, Jingchao Zhou, Zhifeng Li, and Wei Liu. Cosface: Large margin cosine loss for deep face recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 5265–5274, 2018b.

Jiang Wang, Yang Song, Thomas Leung, Chuck Rosenberg, Jingbin Wang, James Philbin, Bo Chen, and Ying Wu. Learning fine-grained image similarity with deep ranking. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1386–1393, 2014.

Kilian Q Weinberger and Lawrence K Saul. Distance metric learning for large margin nearest neighbor classification. *Journal of machine learning research*, 10(2), 2009.

Yandong Wen, Kaipeng Zhang, Zhifeng Li, and Yu Qiao. A discriminative feature learning approach for deep face recognition. In *European conference on computer vision*, pp. 499–515. Springer, 2016.

Ryota Yoshihashi, Wen Shao, Rei Kawakami, Shaodi You, Makoto Iida, and Takeshi Naemura. Classification-reconstruction learning for open-set recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4016–4025, 2019.

Baosheng Yu and Dacheng Tao. Deep metric learning with tuplet margin loss. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 6490–6499, 2019.

Yuhui Yuan, Xilin Chen, and Jingdong Wang. Object-contextual representations for semantic segmentation. In *16th European Conference Computer Vision (ECCV 2020)*, August 2020. URL https://www.microsoft.com/en-us/research/publication/object-contextual-representations-for-semantic-segmentation/.

Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Scene parsing through ade20k dataset. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 633–641, 2017.

Bolei Zhou, Hang Zhao, Xavier Puig, Tete Xiao, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Semantic understanding of scenes through the ade20k dataset. *International Journal of Computer Vision*, 127(3):302–321, 2019.

A Feature Visualization

We visualized the features of 10 foreground classes and the background class in PASCAL VOC. The features are extracted by the DeepLabV3++ours method. We take each pixel of the feature map before classification layer as a feature vector.

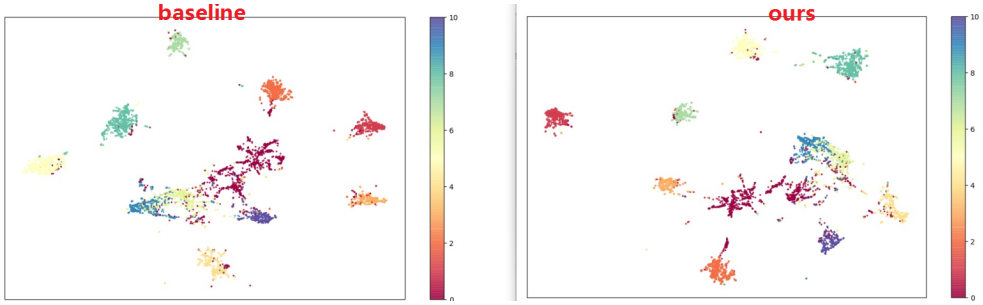

Figure 2: Feature visualization for 10 foreground classes and the background class in PASCAL VOC.