Introducing One Sided Margin Loss for Solving Classification Problems in Deep Networks

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Abstract

This paper introduces a new loss function, OSM (One-Sided Margin), to solve maximum-margin classification problems effectively. Unlike the hinge loss, in OSM the margin is explicitly determined with corresponding hyperparameters and then the classification problem is solved. In experiments, we observe that using OSM loss leads to faster training speeds and better accuracies than binary and categorical cross-entropy in several commonly used deep models for classification and optical character recognition problems.

OSM has consistently shown better classification accuracies over cross-entropy and hinge losses for small to large neural networks. It has also led to a more efficient training procedure. We achieved state-of-the-art accuracies for small networks on several benchmark datasets of CIFAR10(98.82%), CIFAR100(91.56%), Flowers(98.04%), Stanford Cars(93.91%) with considerable improvements over other loss functions. Moreover, the accuracies are rather better than cross entropy and hinge loss for large networks. Therefore, we strongly believe that OSM is a powerful alternative to hinge and cross-entropy losses to train deep neural networks on classification tasks.

1 Introduction

In the past decade, neural networks have made a significant progress for different classification problems. Since AlexNet (Krizhevsky et al. [2012]), there has been a lot of competition to obtain more accurate neural networks. Deeper and more complex networks (Simonyan and Zisserman [2014]), better optimization algorithms (Reddi et al. [2019]), improved activation functions (Rakhlin et al. [2018]) and better loss functions (Bonyadi and Reutens [2019]) have been proposed.

Research on the loss function is a hotspot in this area because an appropriate loss function allows for achieving a more accurate model and might lead to a more efficient training procedure (Han and Wu [2017], Bosman et al. [2020]). A well-known loss function, especially in the literature of support vector machines (SVMs), is the hinge loss (Lee et al. [2015]) which is commonly used for maximum-margin classification. The loss function of an SVM classifier is a linear combination of the empirical error and the margin. Both the empirical error and the margin are functions of the weight vector. During the training procedure, this vector must be chosen to optimize both of them simultaneously. The problem with this configuration is that the width of the achieved margin is not guaranteed. This is a common problem with already known maximum margin classifiers.

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In this paper, we propose a novel loss function, called OSM, to guarantee the width of the obtained classification margin. In fact, OSM allows us to first determine the width of the margin and then adjust the parameters such that the classification error is minimized. The binary OSM loss for data point \((x, y)\) is defined in the following equation:

\[
l_{\text{Binary OSM}} = y \max(s - \lambda_{\text{min}}, 0) + \lambda_{\max} \max(\lambda_{\max} - s, 0)(1 - y) + \alpha \max(-s, 0)y
\]  

where \(s = w^T x + b\) is the score, \(y \in \{0, 1\}\) is the label, \(\alpha\) is the Lagrange multiplier, \(\lambda, \lambda_{\text{min}},\) and \(\lambda_{\max}\) are the hyperparameters and \(\lambda_{\max} - \lambda_{\text{min}}\) determines the margin width. A visual explanation of the OSM loss has been shown in Figure 1.

![Figure 1: The margin hyperplanes in OSM loss. The osm loss has a fixed and predefined margin and tries to locate positive data between the hyperplanes A and B and push the negative ones beyond the hyperplane C.](image)

The major contributions of this paper can be summarized as follows:

- We propose OSM loss function to achieve effective maximum margin classifiers for image classification and optical character recognition (OCR) tasks.
- We applied OSM loss on commonly used convolutional neural networks for different image classification datasets.
- We combined OSM with connectionist temporal classification (CTC) loss to achieve a good loss function for OCR problems.
- We provide an extensive set of experiments on several datasets to verify the effectiveness and efficiency of the OSM loss in comparison to hinge and cross entropy loss functions.

## 2 Related Works

A loss function is a measure of how good a prediction model does in terms of being able to predict the expected outcome. In fact, we convert the learning problem into an optimization problem, define a loss function and then adjust the model parameters to minimize the defined loss function. To improve the accuracies on classification tasks, previous works have proposed many loss functions including mean square error \((\text{Chang and Carin} [2006])\), cross-entropy \((\text{CE}) (\text{Kohonen et al.} [1988])\), hinge \((\text{Lee et al.} [2015])\), kullback leibler divergence \((\text{Csiszar} [1975])\), gaussian radial basis function \((\text{RBF}) (\text{Zadeh et al.} [2018])\) and negative log-likelihood \((\text{Lopez-Garcia et al.} [2015])\), perceptrons \((\text{Minsky and Papert} [1969])\) and logarithmic function \((\text{Gasso} [2019])\).

Before the rise of deep neural networks, hinge loss and its variations were the most commonly used loss functions for classification problems \((\text{Hui and Belkin} [2020])\). Different variants of hinge loss were proposed including ramp \((\text{Collobert et al.} [2006])\), pinball \((\text{Huang et al.} [2013])\), rescaled hinge
(Xu et al. [2017]), squared hinge (Lee et al. [2015]), twin hinge (Huang et al. [2018]) and truncated pinball (Shen et al. [2017]). Linear, polynomial, gaussian RBF and hiperbolic tangent SVMs are among the most effective type of max-margin classifiers using hinge loss (Cervantes et al. [2020]).

To train deep neural networks with hinge loss, usually a linear SVM layer is used (Wang et al. [2022]). Although cross-entropy is known as the most popular loss function, linear SVM has shown comparable performances for image classification with deep neural networks (Tang [2013], Goodfellow et al. [2016]).

3 Proposed Method

In this section, we explain the core idea behind the OSM loss function. Let’s assume that \( x \) is input data and \( y \in \{0, 1, \ldots, C - 1\} \) is the corresponding class label. Consider the function \( f \) maps \( x \) to an output vector \( s = f(x) \in \mathbb{R}^C \) which represents the scores of different classes. In the context of deep neural networks, \( f \) is the network and \( s \) is the final score vector. For simplicity, let’s first consider the 2-class problem, i.e. \( y \in \{0, 1\} \) and \( s \in \mathbb{R} \). The one sided margin loss function, for a single input data, is computed as:

\[
l_{\text{Binary OSM}} = y \max (s - \lambda_{\min}, 0) + \lambda \max (\lambda_{\max} - s, 0) (1 - y) \quad \text{s.t. } ys \geq 0
\]  

(2)

where, \( \lambda_{\max} > \lambda_{\min} \geq 0 \) and \( \lambda > 0 \) are the hyperparameters.

When \( y = 0 \), the condition \( ys \geq 0 \) is satisfied and when the output score is greater than or equal to \( \lambda_{\max} \), the loss function becomes zero and a score less than \( \lambda_{\max} \) causes a nonzero loss. When \( y = 1 \), the condition \( ys \geq 0 \) means that \( s \) must be non-negative and the loss function also tries to get \( s \) closer to \( \lambda_{\min} \). In other words, a positive \( s \) less than or equal to \( \lambda_{\min} \) makes the loss function zero.

If we ignore the constraint of the OSM loss, it becomes very similar to the hinge loss used in SVMs. Unlike the SVM loss function, which utilizes the regularization term \( ||u|| \) to enforce the margin in the final feature space, our loss considers a predefined fixed margin. As explained in Figure 1, the OSM loss tries to locate the positive data between the hyperplanes \( A(0) \) and \( B(\lambda_{\min}) \) and push the negative ones beyond the hyperplane \( C(\lambda_{\max}) \). It is straightforward to add the constraint term to the loss function as a Lagrange multiplier.

In the OSM loss, the scale of input data isn’t important and no specific normalization is needed. This desired characteristic is achieved because the norm of the weight vector is not used in the loss, unlike the SVMs. For example, if the input feature is scaled using matrix \( A \) the final hyperplane is also scaled similarly.

The multiclass OSM loss is defined in (3):

\[
l_{\text{OSM}} = \max (s_y - \lambda_{\min}, 0) + \alpha \max (-s_y, 0) + \lambda \sum_{j \neq y} \max (\lambda_{\max} - s_j, 0)
\]  

(3)

where \( s_y \) is the score of the true class.

Until now, we have defined the hard version of the OSM loss function with a difficult optimization process due to using the \( \max(\cdot) \) function. We also propose the soft version of the OSM loss by replacing \( \max(\cdot, 0) \) with \( \log(1 + \exp(\cdot)) \), as depicted in (4):

\[
l_{\text{soft-OSM}} = \log (1 + e^{s_y - \lambda_{\min}}) + \alpha \log (1 + e^{-s_y}) + \lambda \sum_{j \neq y} \log (1 + e^{\lambda_{\max} - s_j})
\]  

(4)

According to (5), we can assume that OSM loss maximizes the logarithm of the unnormalized probabilities of classes. So, the normalized probability of assigning label \( k \) to input data \( x \) can easily be computed by using \( \log p(y=k|x) = -l_{\text{soft-OSM}} + c \), \( k \in \{0, 1, 2, \ldots, C - 1\} \), where \( c \) is an arbitrary normalization constant. With this configuration of loss function, it is also possible to consider a rejection class. In other words, when the probabilities of all classes are small, we assume
that the data belongs to an extra class called rejection class ($C$). The probability of rejection is defined as follows:

$$\log p(y = C \mid x) = \lambda \sum_j \log \left( 1 + e^{\lambda_{\text{max}} - s_j} \right)$$

(5)

Although in classification tasks, there is no need to use the above defined probabilities, because the class with minimum score $s$ is chosen as the prediction, it might be very useful for many other tasks. For example, in the OCR tasks, unnormalized probabilities can be calculated before feeding the scores into the CTC loss function and also the consider the blank character as the rejection class.

4 Experimental Results

In this section, we conduct different experiments with OSM loss for image classification and OCR tasks. Different deep neural networks are examined over various image classification datasets in Section 4.1. We also analyze the combination of OSM and CTC losses for OCR tasks in Section 4.2.

4.1 Image Classification

This section contains the comparison of the proposed OSM loss with cross-entropy and hinge loss functions on different networks over well-known image datasets.

4.1.1 Implementation Details

To optimize all examined loss functions, we utilize stochastic gradient descent (SGD) with the configurations shown in Table 1. The initial value of the learning rate is 0.01 and it is iteratively updated according to the cosine annealing with warmup scheduler (Loshchilov and Hutter [2016]) that restarts the learning rate 100 epochs. The learning rate plot is shown in Fig 2.

As shown in Table 1, some of the parameters are common among cross-entropy, hinge, and OSM loss functions and hyperparameters $\alpha$, $\lambda$, $\lambda_{\text{min}}$, and $\lambda_{\text{max}}$, are specific to the OSM loss and $\alpha$ is specific to hinge loss. We have reported the average output of 3 runs for each experiment.

| Loss function | Parameter       | Value   |
|---------------|----------------|---------|
| Hinge, CE and OSM | Epoch | 300     |
|                | Optimizer     | SGD+Momentum |
|                | Momentum      | 0.9     |
|                | Regularization| L2      |
|                | Weight Decay  | 0.0005  |
|                | Batch size    | 32      |
|                | Initial Learning Rate | 0.01 |
| Hinge          | $\alpha$      | 1       |
| OSM            | $\alpha$      | 0.1     |
|                | $\lambda$     | 1       |
|                | $\lambda_{\text{max}}$ | 600  |
|                | $\lambda_{\text{min}}$ | 100  |

4.1.2 Datasets & Architectures

In this experiment, we have examined 5 state-of-the-art convolutional architectures including VGG16 (Simonyan and Zisserman [2014]), EfficientNetB0 (Tan and Le [2019]), EfficientNetV2-S, EfficientNetV2-M and EfficientNetV2-L (Tan and Le [2021]) on 4 benchmark datasets including CIFAR10 (Krizhevsky et al. [2009]), CIFAR100 (Krizhevsky et al. [2009]), Stanford Cars (Krause et al. [2013]) and Flowers (Nilsback and Zisserman [2008]). Detailed information about each dataset is shown in Table 2. Table 3 presents details about different convolutional architectures.
4.1.3 Evaluation Metric

Different metrics such as F1-Score, accuracy, precision and recall be used to compare the models obtained by every loss function. In this experiment, we use accuracy as a common evaluation criterion:

\[
\text{Accuracy} = \frac{\text{TruePositive} + \text{TrueNegative}}{\text{Total}}
\]  

4.1.4 Results

To determine the appropriate values for hyperparameters of OSM loss, we trained a VGG16 network with different configurations on CIFAR10 dataset as shown in Table 4. According to the obtained results, we set \( \lambda \) to 1, \( \alpha \) to 0.1, \( \lambda_{\text{max}} \) to 600 and \( \lambda_{\text{min}} \) to 100.

As shown in Table 5 and Fig 3, the training procedure of OSM converges faster and achieves better accuracy in comparison to other loss functions. For example, for EfficientNetB0 trained on CIFAR-10, OSM achieves an accuracy about 1.01% better than cross-entropy and 1.25% better than hinge loss. Some interesting observations about OSM can be summarized as follows:

- In general, in all models and datasets, the accuracy of the OSM loss function is higher than others, for example, an improvement about 0.45% on CIFAR10. In other words, OSM loss consistently results in classifiers better than or equal to the ones obtained by other loss functions.
- For smaller datasets, there is a bigger gap between OSM and the other loss functions. For example, for the EfficientNetB0 network, the accuracy on the CIFAR10 dataset with 10 classes has increased about 1.01%, while it is about 0.6% for CIFAR100 with 100 classes. The improvement is a bit smaller (0.41) for the Stanford Cars dataset with 196 classes.
- For small networks, OSM depicts a bigger improvement in accuracy than the obtained improvement for large networks. For example, on the CIFAR10 dataset, OSM has shown an improvement about 1.01% while its improvement for the EfficientNetV2-L network 0.15%.
- Along with better accuracies, OSM has demonstrated a faster training procedure compared to cross-entropy. For the VGG16 model on the CIFAR10 dataset, the OSM loss function
Table 3: Image classification architectures

| Model                              | Parameters |
|------------------------------------|------------|
| VGG16 [Simonyan and Zisserman 2014] | 138.4M     |
| EfficientNetB0 [Tan and Le 2019]   | 5.3M       |
| EfficientNetV2-S [Tan and Le 2021] | 21.6M      |
| EfficientNetV2-M [Tan and Le 2021] | 54.4M      |
| EfficientNetV2-L [Tan and Le 2021] | 119.0M     |

Table 4: Comparison of the effect of hyperparameters on the OSM loss function

| α  | λ   | λ_{max} | λ_{min} | Accuracy |
|----|-----|---------|---------|----------|
| 0.01 | 1   | 600     | 100     | 90.65    |
| 0.1  | 1   | 600     | 100     | 92.77    |
| 1    | 1   | 600     | 100     | 92.14    |
| 5    | 1   | 600     | 100     | 91.65    |
| 10   | 1   | 600     | 100     | 91.19    |
| 0.1  | 0.01 | 600       | 100     | 91.08    |
| 0.1  | 0.1  | 600     | 100     | 92.43    |
| 0.1  | 1    | 600     | 100     | 92.77    |
| 0.1  | 5    | 600     | 100     | 91.82    |
| 0.1  | 10   | 600     | 100     | 90.94    |
| 0.1  | 1    | 1000    | 0       | 91.75    |
| 0.1  | 1    | 700     | 0       | 92.09    |
| 0.1  | 1    | 500     | 0       | 92.68    |
| 0.1  | 1    | 300     | 0       | 92.13    |
| 0.1  | 1    | 100     | 0       | 91.89    |
| 0.1  | 1    | 900     | 400     | 92.49    |
| 0.1  | 1    | 800     | 300     | 92.55    |
| 0.1  | 1    | 700     | 200     | 92.61    |
| 0.1  | 1    | 600     | 100     | 92.77    |
| 0.1  | 1    | 500     | 0       | 92.63    |

has achieved the accuracy 92.53% in epoch 139 while cross-entropy has achieved the same accuracy after 237 epochs.

- As explained in the previous section, all hyperparameters are adjusted in a general fashion, i.e. from the training of VGG16 on CIFAR10. It is obvious that adjusting the hyperparameters for each dataset will result in better performance.

- It can be also observed that cross-entropy loss is always better than hinge loss for all models and datasets.

4.2 Optical Character Recognition

In this section, the common CTC loss will be compared with the combined OSM-CTC loss in which, instead of scores, normalized probabilities obtained from OSM are fed into CTC. Both loss functions are examined on the license plate number recognition problem. During this experiment, the blank character is assumed as the rejection class.

4.2.1 Implementation Details

Two optical character recognition models are implemented using TensorFlow version 1.15.0. The initial value of the learning rate is 0.001. When using OSM layer before CTC loss, like the classification problem, cosine annealing with warmup has been used to change the learning rate in different epochs. For common CTC loss, the cosine annealing scheduler didn’t show a good performance but the exponential decay scheduler has shown a very better performance. The values of common CTC and OSM hyper-parameters and OSM-specific hyper-parameters are shown in Table 6.
Table 5: Comparison between networks and datasets (EffNet is the abbreviation of EfficientNet).

| Dataset           | Loss Function | VGG16 | EffNetB0 | EffNetV2-S | EffNetV2-M | EffNetV2-L |
|-------------------|--------------|-------|----------|------------|------------|------------|
| CIFAR10           | OSM          | 92.77 | 98.53    | 98.82      | 99.01      | 99.05      |
|                   | CE           | 92.53 | 97.52    | 98.19      | 98.78      | 98.90      |
|                   | Hinge        | 92.38 | 97.28    | 98.10      | 98.02      | 98.12      |
| Improvement       |              | 0.24  | 1.01     | 0.63       | 0.23       | 0.15       |
| CIFAR10 (Plane,Truck) | OSM      | 98.59 | 99.54    | 99.60      | 99.66      | 99.78      |
|                   | Binary CE    | 98.43 | 99.10    | 99.23      | 99.50      | 99.71      |
|                   | Hinge        | 98.12 | 98.72    | 98.97      | 99.03      | 99.21      |
| Improvement       |              | 0.16  | 0.44     | 0.37       | 0.16       | 0.07       |
| CIFAR100          | OSM          | 71.38 | 88.41    | 91.56      | 92.25      | 92.20      |
|                   | CE           | 71.29 | 87.81    | 91.17      | 92.08      | 92.12      |
|                   | Hinge        | 70.88 | 87.38    | 90.88      | 91.65      | 91.78      |
| Improvement       |              | 0.09  | 0.60     | 0.39       | 0.17       | 0.08       |
| Flowers           | OSM          | 87.36 | 97.13    | 98.04      | 98.51      | 98.69      |
|                   | CE           | 87.14 | 96.62    | 97.61      | 98.35      | 98.64      |
|                   | Hinge        | 86.43 | 96.19    | 97.03      | 97.92      | 98.02      |
| Improvement       |              | 0.22  | 0.51     | 0.43       | 0.16       | 0.05       |
| Stanford Cars     | OSM          | 88.02 | 91.06    | 93.91      | 94.50      | 94.99      |
|                   | CE           | 87.96 | 90.65    | 93.53      | 94.41      | 94.95      |
|                   | Hinge        | 87.19 | 90.21    | 92.92      | 94.13      | 94.67      |
| Improvement       |              | 0.06  | 0.41     | 0.38       | 0.09       | 0.04       |

Figure 3: Comparison accuracy on CIFAR10, training on VGG16

4.2.2 Datasets & Architectures

In this task, we used the LPRNet architecture (Zherzdev and Gruzdev [2018]), which is a real-time license plate recognition network and is trained end-to-end. The CCPD (Chinese City Parking Dataset) (Xu et al. [2018]) dataset is also used to train and evaluate the LPRNet model. The number of training and validation data are 100000 and 99996, respectively. We considered both the basic LPRNet and its scaled-down version with fewer parameters. In the scaled-down version, the number of channels is reduced from 64 to 16, and the channel increasing coefficient is halved.
Table 6: Hyperparameter of neural networks in optical character recognition experiments

| Loss function | Parameter     | Value     |
|---------------|---------------|-----------|
| CTC and CTC-OSM | Epoch        | 300       |
|               | Optimizer     | Adam      |
|               | Batch size    | 60        |
|               | Initial Learning Rate | 0.001    |
| OSM           | $\alpha$      | 1         |
|               | $\lambda$     | 1         |
|               | $\lambda_{\text{max}}$ | 600    |
|               | $\lambda_{\text{min}}$ | 100    |

4.2.3 Evaluation Metric

In order to evaluate the optical character recognition quantitatively, the ratio of correctly recognized plates to the total number of license plates is computed (Equation. (7)). The greedy decoder was used to generate the output sequence of characters. The greedy decoder is very straightforward because the letter with the highest probability is selected at each time step.

$$\text{Acc}_{\text{OCR}} = \frac{\text{The number of correctly recognized license plates}}{\text{Total number of license plates}} \quad (7)$$

4.2.4 Results

Table 7 shows the accuracies obtained by the OSM-CTC and CTC loss functions. Although OSM loss function achieves better accuracies for both models, its improvement is more significant (1.8%) for the smaller model.

Table 7: Comparasion between OSM-CTC and CTC

| Model - Loss function | CTC | OSM |
|-----------------------|-----|-----|
| scaled-down LPRNet model | 0.958 | 0.976 |
| LPRNet model          | 0.99 | 0.995 |

5 Conclusion

We proposed a novel loss function called OSM that creates a fixed margin for the decision boundaries between different classes. It is very straightforward and intuitive to set the hyperparameters of OSM loss. Extensive experiments show that OSM achieves better results with different network architectures on benchmark datasets compared to other well-known loss functions, in both image classification and OCR tasks. According to experiments, OSM loss demonstrates a bigger improvement for smaller networks. Also, the probabilities produced by OSM improved the performance of the OCR task especially when the model is scaled down.

5.1 Extensions

Since OSM loss leads to big improvements over hinge and cross entropy loss functions for small architectures, it is definitely the best choice to run deep models on low resource and embedded devices. OSM loss might also be helpful for other vision tasks like object detection. It can also be applied on audio and text classification tasks.

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