Can data placement be effective for Neural Networks classification tasks? Introducing the Orthogonal Loss

B. Cancela, V. Bolón-Canedo & A. Alonso-Betanzos

Laboratory for Research and Development in Artificial Intelligence (LIDIA),
CITIC Research Center, University of A Coruña, Spain

Introduction

Cross-entropy classification loss aims to separate the deep features between classes as much as possible:

- It does not matter where the deep features are placed, as long as they are clearly separated.
- Softmax score establishes how confident we are that an input belong to one class **compared to the other classes**.

This paper presents **two main contributions:**

- Two loss functions that aim to avoid deep features to appear in the projection of the wrong class. They need the last layer to be fixed during training (preferably orthogonal).
- A variant to the softmax function, aiming to provide a more accurate label confidence.

Exponential Orthogonal Loss

- $\tilde{y}^{(i)}$: model prediction
- $y^{(i)}$: input label (one-hot encoding)

$$\mathcal{L}^{EOL}(\tilde{y}^{(i)}, y^{(i)}) = \sum \overbrace{y^{(i)}\ e^{R-\tilde{y}^{(i)}}}^{\mathcal{L}^{EOL}_{pos}} + \lambda\ \underbrace{(1-y^{(i)})\ (\tilde{y}^{(i)})^2}_{\mathcal{L}^{EOL}_{neg}}, \quad R > 0,$$

Trench Orthogonal Loss

- $\tilde{y}^{(i)}$: model prediction
- $y^{(i)}$: input label (one-hot encoding)

$$\mathcal{L}^{TOL}(\tilde{y}^{(i)}, y^{(i)}) = \sum \overbrace{y^{(i)}\ (R-\tilde{y}^{(i)})^2}^{\mathcal{L}^{TOL}_{pos}} + \lambda\ \underbrace{(1-y^{(i)})\ (\tilde{y}^{(i)})^2}_{\mathcal{L}^{TOL}_{neg}}, \quad R > 0,$$

Softmax variant

- $\tilde{y}^{(i)}$: model prediction
- Checks how good is the projection in each class.

$$p(\tilde{y}^{(i)}) = \frac{\max(0, \tilde{y}^{(i)})}{\max(P, \sum \max(0, \tilde{y}^{(i)}))}, \quad P > 0.$$

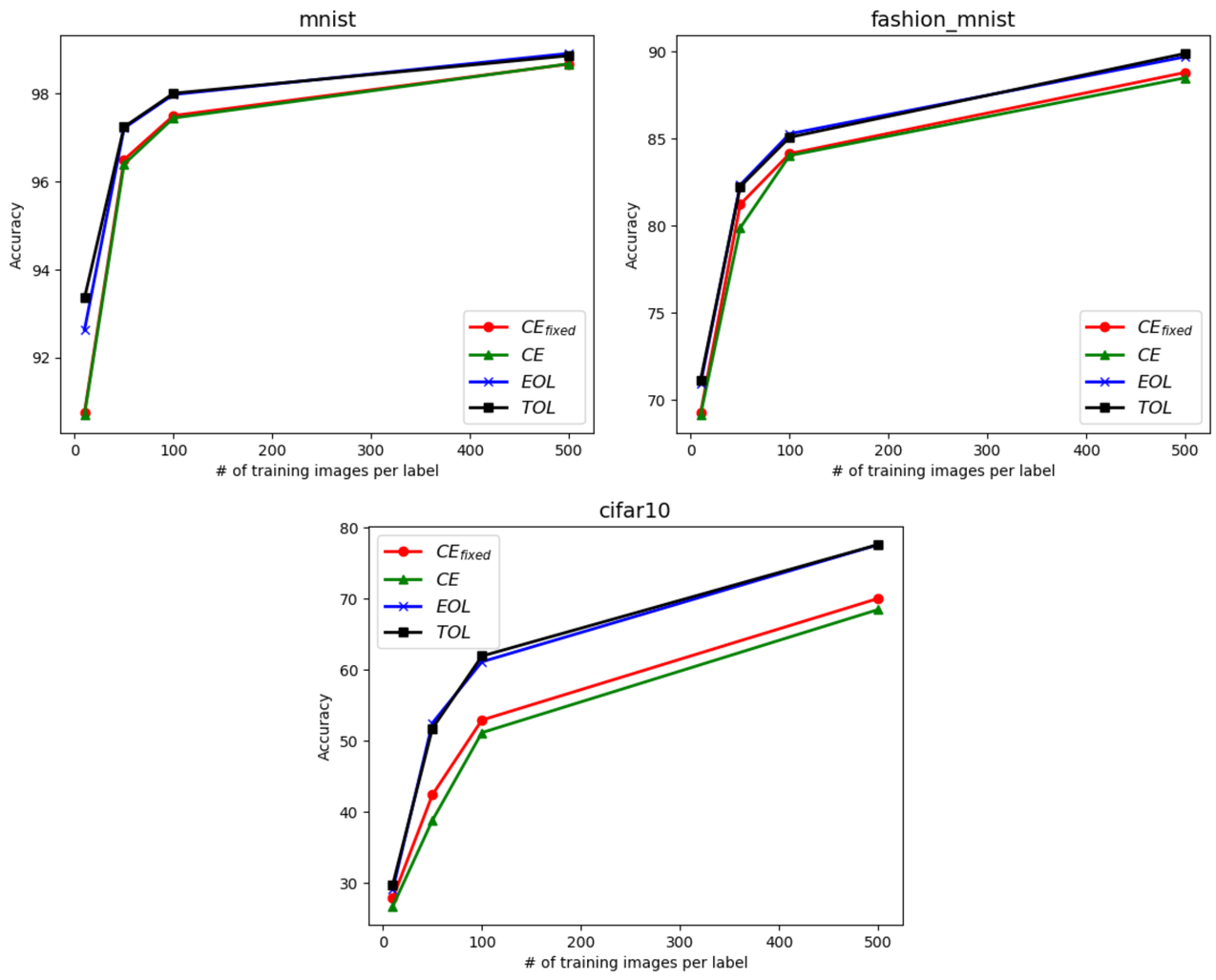
Experimental Results on Loss Functions

- Tested in 5 different datasets using two networks.
- The results are better than using the cross-entropy loss.

WRN-16-4	CE (fixed classifier)	CE	EOL	TOL
MNIST	99.67 ± 0.02	99.64 ± 0.02	99.64 ± 0.02	99.66 ± 0.01
Fashion-MNIST	95.31 ± 0.10	95.26 ± 0.14	$\mathbf{95.47 \pm 0.13}$	95.21 ± 0.18
CIFAR-10	94.59 ± 0.13	94.59 ± 0.17	$\mathbf{94.88 \pm 0.13}$	94.75 ± 0.10
CIFAR-100	74.95 ± 0.09	74.70 ± 0.24	74.92 ± 0.09	$\mathbf{75.39 \pm 0.18}$
STL-10	86.19 ± 0.35	85.70 ± 0.21	$\mathbf{86.65 \pm 0.34}$	$\mathbf{86.71 \pm 0.28}$

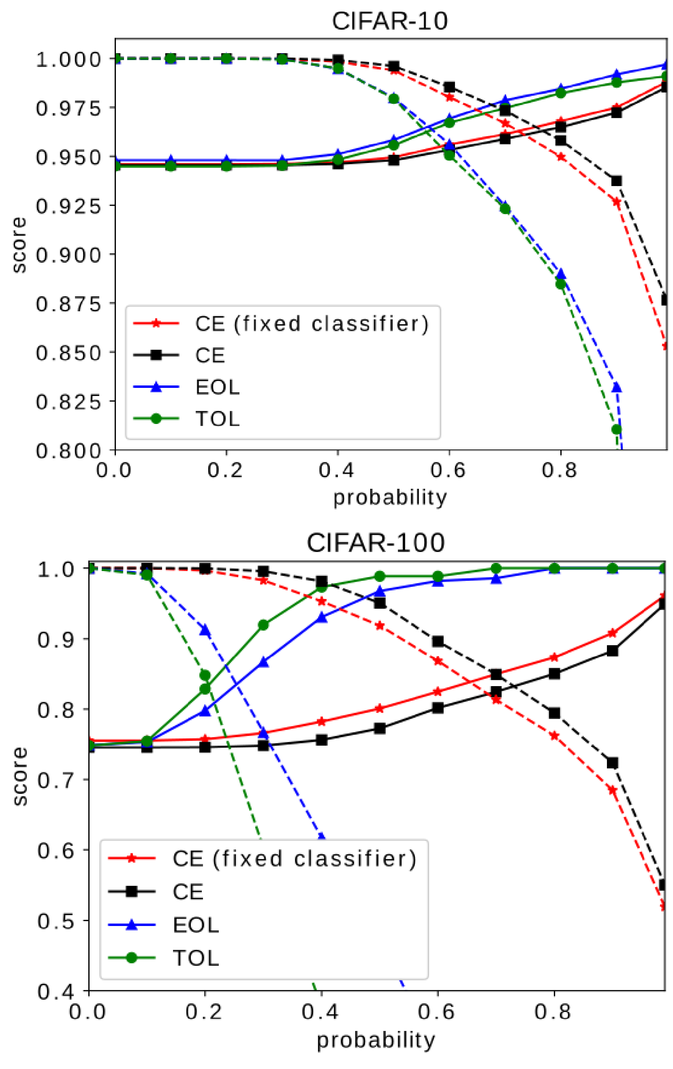
VGG	CE (fixed classifier)	CE	EOL	TOL
MNIST	99.57 ± 0.01	99.57 ± 0.04	99.57 ± 0.06	$\mathbf{99.64 \pm 0.01}$
Fashion-MNIST	94.26 ± 0.13	94.27 ± 0.07	$\mathbf{94.35 \pm 0.05}$	$\mathbf{94.45 \pm 0.14}$
CIFAR-10	91.70 ± 0.13	91.55 ± 0.17	$\mathbf{92.03 \pm 0.13}$	$\mathbf{91.82 \pm 0.12}$
CIFAR-100	66.38 ± 0.67	63.13 ± 0.80	$\mathbf{69.95 \pm 0.19}$	$\mathbf{69.90 \pm 0.34}$
STL-10	79.78 ± 0.56	78.27 ± 0.23	$\mathbf{81.39 \pm 1.08}$	$\mathbf{80.44 \pm 0.79}$

- The difference against cross-entropy loss is higher when reducing the training size.



Results on the Softmax Variant

- Whenever the confidence in is high, our variant is less prone to assign a wrong class.



Conclusions

- Deep features can be effectively placed without losing performance (sometimes even better).
- It obtains better results when the number of training samples is low.
- The softmax variant provides a better degree of certainty in the probability outputs.
- Deep features placed in orthogonal projections have interesting properties.

— 25th International Conference on Pattern Recognition 2021 —