Mixup training

Analysis of the impact on calibration of deep neural networks

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Introduction

Motivation

Although modern DNN show an increase in accuracy they face major calibration issues.

Mixup is a recently proposed method to reduce overconfidence in image classification and decision making DNN, improving overall calibration.

The method is both effective and simple to implement.[2]

New samples are generated during training as a convex combination of random pairs of images and their labels.

Methods used - Data set

Mixup is based on *Vicinal Risk Minimization* principle.

From randomly selected images x_i, x_j and labels y_i, y_j we generate vicinial points $\tilde{x}, \tilde{y}$ as

$$\tilde{x} = \lambda x_i + (1 - \lambda) x_j$$
$$\tilde{y} = \lambda y_i + (1 - \lambda) y_j$$

We then train the network on these vicinial points.

Methods used - Loss function

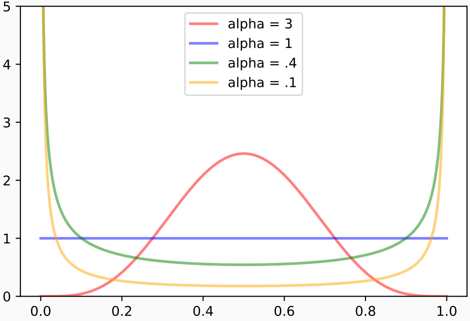
For training the network on the mixup data set we used a new mixup criterion, inspired by [2], using the *Cross Entropy Loss* $\mathcal{L}$ and the same notations

$$\tilde{\mathcal{L}}(\tilde{x}, \tilde{y}) = \lambda \mathcal{L}(\tilde{x}, y_i) + (1 - \lambda) \mathcal{L}(\tilde{x}, y_j).$$

Methods used - λ parameter

The interpolating factor $\lambda \in [0, 1]$ is drawn from the symmetric beta distribution with chosen parameter α. We used values of α from 0.1 to 0.4, proven to show best results.[3]

λ determines the mixing ratio, $\lambda = 0, 1$ corresponds to the original minimisation.



Calibration Metric

For calibration we used the *Expected Calibration Error* metric as proposed in [1][2]. It can be written as

$$ECE = \sum_{m=1}^{M} \frac{|B_m|}{n} |acc(B_m) - conf(B_m)|,$$

where B_m are equally spaced bins for the predictions over n samples.

Implementation on CIFAR-10

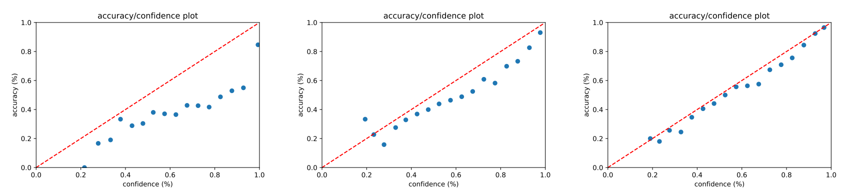
Implementation

For our implementation we first used a wide network `wide_resnet50_2` and then moved on to `resnet18`, yielding better results.

We used the *SGD* optimiser with learning rate 0.003 and momentum 0.9. The criterion used is the *Cross Entropy Loss*.

The model achieved $\sim 70\%$ accuracy on all different instances. We noticed a small difference, roughly less than 2%, between no mixup and the most efficient mixup ($\alpha = 0.4$).

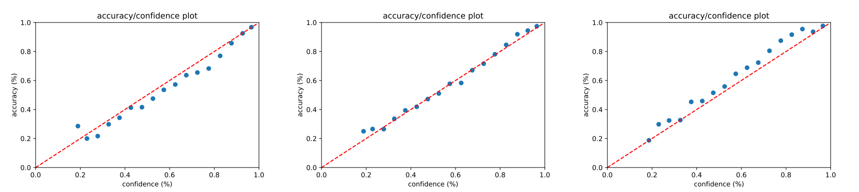
Results



$\alpha = 0,\ ECE = 0.19559$ $\alpha = 0.1,\ ECE = 0.08888$ $\alpha = 0.2,\ ECE = 0.03203$

Figure 1: Accuracy/confidence plot for several α values

Results



$\alpha = 0.3,\ ECE = 0.03127$ $\alpha = 0.4,\ ECE = 0.01761$ $\alpha = 0.7,\ ECE = 0.06188$

Figure 2: Accuracy/confidence plot for several α values

Conclusion

Questions?

References

- Chuan Guo et al. *On Calibration of Modern Neural Networks.* 2017. arXiv: *1706.04599 [cs.LG]*.
- Sunil Thulasidasan et al. *On Mixup Training: Improved Calibration and Predictive Uncertainty for Deep Neural Networks.* 2020. arXiv: *1905.11001 [stat.ML]*.
- Hongyi Zhang et al. "mixup: Beyond Empirical Risk Minimization". In: *CoRR* abs/1710.09412 (2017). arXiv: *1710.09412*. URL: *http://arxiv.org/abs/1710.09412*.