# Opposition Deba

Filip Cornell

May 24, 2021

I opposed Deba, who presented papers mainly about *calibration* of neural networks, in other words the problem of having networks reflecting a true uncertainty in their predictions.

## 1 Content

Deba chose three papers. The first paper, *On Calibration of Modern Neural Networks* [1] discusses 3 main reasons (increased model capacity, batch normalization and less explicit regularization, specifically $l_2$-regularization) why modern neural networks. Furthermore, they introduce a technique, temperature scaling, which learns a single parameter $T$ on a validation set to recalibrate a neural networks to make it more calibrated.

The second paper, *Verified Uncertainty Calibration* [2] shows that techniques such as temperature scaling are less calibrated than they show, and it is not possible to say how calibrated they actually are. Theoretical justifications show that methods such as temperature scaling are optimistic estimators of the uncertainty, which is of course not desirable, and they therefore develop a new method that mitigates these issues. This method can not only perform better, but it can also give information on how calibrated they actually are. They do this by combining two previously existing approaches; histogram binning and platt scaling, and adopting the best characteristics from both; histogram binning [5] and platt scaling [3].

The last paper, Learning for single-shot confidence calibration in deep neural networks through stochastic inferences [4]. It proposes a new way of calibrating neural network through a single pass by using stochastic methods, and shows its superority in comparison to previous methods such as temperature scaling [1]. This does not require a separate validation set onto which one optimizes the calibration, and is therefore highly beneficial in this sense.

## 2 Suitability of the chosen papers

The suitability for this course can be put into question, as none of the papers focus on what has been described as the focus of the course (algorithms and system on large scale graph processing, stream processing, social network analytics and decentralized machine learning). However, I think it is still appropriate as this is Deba's personal focus in his research, and I think it brings a certain amount of diversity into what we have discussed in this course. It was therefore however also hard for me to oppose since the area was completely new to me, but Deba did a good job in presenting the papers.

# 3 Links between the papers

The link between the papers was very clear as they all treat the same problem; calibrating neural networks towards reflecting true uncertainties in their predictions. They all propose different solutions and state different problems in both actual architectures and other methods for calibrating neural networks.

# 4 Quality of presentation

Deba's way of talking was very intuitive and pedagogical. It was easy to follow what he was saying and he explained things in simple terms, allowing most people to understand the topic despite not having the proper background. However, I think the presentation was too long (although to be fair, he was interrupted several times for questions during his presentation). I think he could have planned the time better; he also could have used more visual slides and less equations. Given that the area was new to us all, I think it would have served us well with more visual slides and less equations. However, as I mentioned, I think he orally explained things very well and in simple terms, so by listening, it was easy to understand and follow.

# References


[1] Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. On calibration of modern neural networks. In *International Conference on Machine Learning*, pages 1321–1330. PMLR, 2017.

[2] Ananya Kumar, Percy Liang, and Tengyu Ma. Verified uncertainty calibration. *arXiv preprint arXiv:1909.10155*, 2019.

[3] John Platt et al. Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods. *Advances in large margin classifiers*, 10(3):61–74, 1999.

[4] Seonguk Seo, Paul Hongsuck Seo, and Bohyung Han. Learning for single-shot confidence calibration in deep neural networks through stochastic inferences. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9030–9038, 2019.

[5] Bianca Zadrozny and Charles Elkan. Obtaining calibrated probability estimates from decision trees and naive bayesian classifiers. In *Icml*, volume 1, pages 609–616. Citeseer, 2001.