





The problem

Figure: Prediction confidence vs accuracy of classic and modern neural network, obtained from [1].

Modern neural networks are poorly calibrated meaning the predicted probabilities do not correspond to the observed accuracy.

Measuring Calibration





Figure: Calibration plots for Dropout Variational Inference (left) and Bayesian Dark Knowledge (right).

Calibration of a classifier can be measured by binning predictions over confidence levels and comparing the observed and predicted accuracies for the respective confidence levels.





Figure: Uncertainty estimates of a Neural Net with ML inference and and Bayesian Inference methods.

Approximate Bayesian Inference methods significantly improve uncertainty estimates. However, performance and bias are a problem. Bayesian Dark Knowledge [2] uses studentteacher training to summarise the posterior

predictive in a single network which allows constant time inference.

Dropout Variational inference with α -divergences requires only a small modification to the loss function compared to ML inference [3].

Well-Calibrated Bayesian Neural Networks

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Dropout Variational Inference

$$\mathcal{L}(\theta) = \beta \theta^T \theta - \frac{1}{\alpha} \frac{N}{n} \sum_{i=1}^n p(X_i | \theta)^{\alpha}$$

gradient HMC.

(2017). On Calibration of Modern Neural Networks. *ArXiv*. [2] Korattikara, A., Rathod, V., Murphy, K., & Welling, M. (2015). Bayesian Dark Knowledge. [3] Li, Y., & Gal, Y. (2017). Dropout Inference in **Bayesian Neural Networks with Alpha**divergences. ArXiv.

Stochastic gradient MCMC



Figure: Metropolis-Hasting (blue), Barker (orange), and noise adaptive acceptance test (green).

The noise adaptive acceptance test is a novel approach to reduce the bias of stochastic

A tradeoff is made between sample efficiency and acceptance error.

References

[1] Guo, C., Pleiss, G., Sun, Y., & Weinberger, K. Q.