## Advanced Data Mining Reading Course

Final Report

Ву

## Vangjush Komini

vangjush@kth.se



 $June\ 8,\ 2021$ 

1 Self review

The first paper [3] utilizes two key drivers to model the uncertainty present in the data. Namely, the dynamic estimation of the mean for each of the classes and a radial basis function (RBF) that measures the distances of a test item from each of these estimated means. The uncertainty is then computed by the distance of the test item to the closes mean in the embedding space. Their success comes at the expense of two important hyper-parameters: the RBF width and the double-backpropagation coefficient.

The second paper [1] parameterizes the uncertainty of the predictive output by utilizing a parametric distribution of the predictive output. If the model is a classifier, the authors proposed estimating a Dirichlet distribution that acts as a distribution over distribution. If the model is a regressor, the predictive output is modeled through a Gaussian distribution. However, its supportive mean and variances are not deterministic values by modeled using two additional auxiliary distributions, a gamma, and another Gaussian, respectively. Eventually, by doubling the number of the parameters at the final layer, it is possible to accommodate the uncertainty and have a single run at the test time.

The last paper [2] manages to estimate the uncertainty of the predictive response in a single run by predicting multiple different outputs from different depths of the model. Operating under the assumption that the model's depth should have minor changes in the embedding projection, these outputs are aggregated to estimate the uncertainty empirically. Furthermore, to train the model using the empirical risk minimization, the likelihood of their predictive response weights the gradients of each layer. The likelihood of the predictive response is itself estimated using variational inference. Eventually, training this model is more reflective of the expectation-maximization setup rather than traditional gradient descent methods.

## References

- [1] Alexander Amini, Wilko Schwarting, Ava Soleimany, and Daniela Rus. Deep evidential regression. *CoRR*, abs/1910.02600, 2019.
- [2] Javier Antorán, James Urquhart Allingham, and José Miguel Hernández-Lobato. Depth uncertainty in neural networks, 2020.
- [3] Joost van Amersfoort, Lewis Smith, Yee Whye Teh, and Yarin Gal. Simple and scalable epistemic uncertainty estimation using a single deep deterministic neural network. *CoRR*, abs/2003.02037, 2020.

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