Exposé BNN Uncertainty

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(Why?) Uncertainty

A trained (deep) Neural Network usually outputs point estimates, which are dependend on its weights. Those predicted outputs are often signed with intransparent confidence, making it bad to depend on, because the performance is hard to assess.

Building on this problem, Bayesian Neural Networks use probability distributions as weight-values, making the network more focused on uncertainty. Also the output moves from a point estimate to a probability distribution. For small networks it is possible to compute the posterior distributions. But in more complex - state of the art - Neural Networks, this task turns into an intractable computation, resulting in the need for approximating the posterior distributions. Using Bayesian methods, this computation gets tractable, making it possible to assign uncertainty to the networks weights and output:

- Laplace Approximations of weights (MacKay 1992, Laplace)
  - for more complex networks: scalable Laplace approximation of weights (Ritter, Botev, and Barber 2018, KFAC)
- Variational Inference (Graves 2011, VI)

Why uncertainty? The training method of a network can be optimized using uncertainty. For example, if it is located deeper in the networks, the training method can focuse on other parts of the network at the beginning. Also the network architecture can be optimized using uncertainty, as it can show if a layer doesnt get identified properly. If so it shouldn't be part of the network at all.

Bayesian Methods / Basic research

Laplace approximation of the weights in Neural Networks

In plain Neural Networks we end up in an optimization-problem, since we want the minimize the Errorfunction. Using Bayesian Neural Networks we move to an integration-problem, because probability distributions are used as weights. Using Bayes theorem the posterior of the weights can be formulated, but is intractable. Using the Laplace's method (MacKay 1992) it can be approximated. This leads us to build a Gaussian around the mode (W_{MAP}) with a curvature that is given by the Hessian:

$$p(W|\mathcal{D}) \approx \mathcal{N}(W_{MAP}, H^{-1})$$

KFAC

Looking at state of the art Neural Networks, with millions of weight-paramaters the method of (MacKay 1992) reaches its limit, because the Hessian gets enormously large. To tacle this problem the Hessian gets approximated by using a Kronecker product of two smaller matrices. The scaled Laplace approximation end up in a multivariate Gaussian and can be represented as:

$$\mathcal{N}(\text{vec}(W_{MAP}), (\mathcal{Q} \otimes \mathcal{H})^{-1})$$

Variational Inference

This method, again, tacles the problem of intractability of the posterior $p(w/\mathcal{D})$. The method essentially approximates the posterior by using a parameterized variate distribution $q(w|\theta)$ of the same functional form and minimizing the difference between $p(w/\mathcal{D})$ and $q(w|\theta)$, making this an optimization-problem. This is done by minimizing the Kullback-Leibler divergence between p and q, while the parameters in q are estimated.
Using this method, $q(w|\theta)$ learns a good representation of the data.

ELBO and reparametrization trick

The VI method can be further optimized using ELBO and the reparametrization trick.
ELBO substantially achieves the same as the KL: minimizing the difference between p and q.
ELBO in maximal when p and q are the same. Using ELBO gives some advantages againts the KL, which will be thematized in the thesis.

The reparametrization trick basically makes it possible to optimize a models parameters, since we can not backpropagate through a stochastic node. By moving the parameters outside of the distribution function, a gradient can be calculated for the parameters.

reference to other possible Bayesian methods

There are also more possible Bayesian methods that yield uncertainty estimates from Neural Networks. They will most likely not be a central part of my thesis, but nevertheless it shows more possibilitys in the field of uncertainty:

- tbd
- tbd
- …

Research Goals/ content of the thesis

Making use of the above methods [(MacKay 1992) and (Graves 2011)] I will try to locate the uncertainty in a more simple network. Next up I will zoom into the network and observate a single layer in terms of uncertainty. To make this more understadable a visualization of the above will be elaborated. I will then move on to a more complex network and try to transfer the findings from the previous steps. Afterward it would be interesting how the uncertainty bahaives during training.

References

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MacKay, David J. C. 1992. „A Practical Bayesian Framework for Backpropagation Networks.“ *Neural Computation* 4 (3): 448–472. doi:`10.1162/neco.1992.4.3.448`. eprint: `https://doi.org/10.1162/neco.1992.4.3.448`. `https://doi.org/10.1162/neco.1992.4.3.448`.

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