Exposé BNN Uncertainty

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29. May 2020

(Why?) Uncertainty

- Problems of DNNs:
  - outputs point estiamates, with intransparent confidence. $\rightarrow$ perfomance is bad to assess.
- Uncertainty:
  - BNNs put probability distributions as weights
  - Baysian methods can compute uncertainty on each weight/ all weights and the networks predictions:
    - Laplace Approximations of weights (MacKay 1992, Laplace)
      - further a scalable Laplace approximation of weights (Ritter, Botev, and Barber 2018, KFAC)
    - Variational Inference (Graves 2011, VI)
  - knowing where the uncertainty is 'located', the training process and network architecture can be optimized.

Bayesian Methods / basic research

Laplace approximation of the weights in neural networks

- plain NNs end up in optimizationproblem, while BNNs move to an integrationproblem
- the posterior gets intractable and needs to be approximated
- by building a Gaussian around the MAP(/mode) with a curvature that is given by the Hessian

KFAC

- plain Laplace approximation à la (MacKay 1992) gets intractable for state of the art neural networks, due to matrix size
- approximate the Hessian by using two smaller matrices
- posterior is approximated as a multivariate Gaussian
- $\mathcal{N}(\text{vec}(W_{MAP}), (\mathcal{Q} \otimes \mathcal{H})^{-1})$

Variational Inference

- here we have an optimazationproblem, again.
- the KL divergence can compute the difference betweeen two distributions
- due to intractability of the porsterior, it can be approximated by a variate distribution $q(w|\theta)$
- $q(w|\theta)$ shares its funcitonal form with the posterior
- goal is to minimize the KL betweeen the posterior and $q(w|\theta)$, while the parameters in $q(w|\theta)$ get estimated
- $q(w|\theta)$ learns a good representation of the data

ELBO and reparam. trick

- ELBO is maximal when p and q are the same. $\rightarrow$ ELBO is the same as minimizing the KL-divergence
- reparam. trick: tbd

reference to other possible Bayesian methods

- given in further literature (not read yet)

Research Goals/ content of the thesis

- locate the uncertainty in a network via Laplace and VI
- visualization of the above
- move from simple networks to more complex and try to transfer the findings
- track the uncertainty while training

Outline

1. tbd
2. tbd
   (a) tbd
   (b) tbd
3. tbd
4. tbd

References

Graves, Alex. 2011. „Practical Variational Inference for Neural Networks.“ In *Advances in Neural Information Processing Systems 24,* edited by J. Shawe-Taylor, R. S. Zemel, P. L. Bartlett, F. Pereira, and K. Q. Weinberger, 2348–2356. Curran Associates, Inc. http://papers.nips.cc/paper/4329-practical-variational-inference-for-neural-networks.pdf.

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.

Ritter, Hippolyt, Aleksandar Botev, and David Barber. 2018. „A Scalable Laplace Approximation for Neural Networks.“ In *International Conference on Learning Representations.* https://openreview.net/forum?id=Skdvd2xAZ.