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Karlsruhe Institute of Technology

Autonome Lernende Roboter (ALR)
Prof. Gerhard Neumann

Project Type _____

- ☑ Master Thesis
- ☐ Bachelor Thesis
- ☐ Research Project

Supervisors _____

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Difficulty _____

Algorithmic

Math

Application

Efficient Gradient-Based Variational Inference with GMMs

Description

In this project, we want to develop a new efficient algorithm for variational inference [2]. In variational inference, we want to approximate a intractable target distribution (often given as a posterior distribution) with a tractable model distribution. Applications of variational inference include learning of posterior distributions in deep neural networks [3] as well posterior distribution over hyper-parameters of other machine learning representations. A common choice for tractable models that are still very flexible are Gaussian mixture models (GMMs). We will extend an algorithm for learning such GMM representations that have been recently developed by our group [1]. The original algorithm is only applicable in the blackbox setup, i.e., where no gradient of the target distribution is available. We will extend this algorithm to also utilize this gradient information which again should considerably increase its speed and scalability. We will apply the resulting algorithm to small-size neural network problems or robot planning problems.
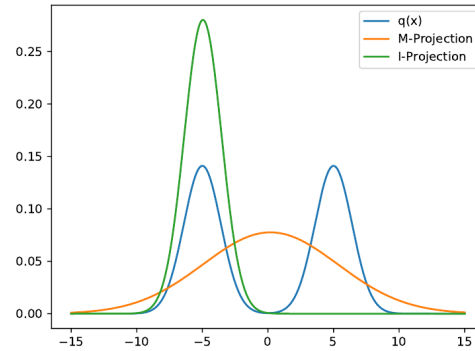

Figure 1: Example of different projections that can be used for variatinoal inference.

Tasks

The tasks in this project will involve:

- Familiarize with original algorithm and implementation: You need to study the VIPS algorithm [1] and the corresponding background material on variational inference. Get used with the existing, highly optimized c++ implementation.
- Extend algorithm with gradient information. The VIPS algorithms needs to be extended such that gradient information can be exploited for the surrogate computation. Moreover, we can improve efficiency of the surrogate by the use of recursive estimation techniques. The existing implementation needs to be extended such that it can take gradients from pytorch.
- Benchmarking and comparisons. The new algorithm needs to be tested and evaluated on multiple machine learning problems such as posterior estimation for deep neural networks and compared against existing methods [3].

References

[1] O. Arenz, M. Zhong, and Neumann G. Trust-region variational inference with gaussian mixture models. *Journal of Machine Learning Research (JMLR)*, 2020.

[2] David M. Blei, Alp Kucukelbir, and Jon D. McAuliffe. Variational inference: A review for statisticians. *Journal of the American Statistical Association*, 112(518):859–877, Apr 2017.

[3] Kazuki Osawa, Siddharth Swaroop, Mohammad Emtiyaz E Khan, Anirudh Jain, Runa Eschenhagen, Richard E Turner, and Rio Yokota. Practical deep learning with bayesian principles. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32, pages 4287–4299. Curran Associates, Inc., 2019.