Karlsruhe Institute of Technology

Autonomous Learning Robots (ALR)

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Project Type

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

Supervisors

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Difficulty

Algorithmic

Math

Application

Investigating the Amortization Gap in Variational Inference for State Space Models

Description

Amortized Variational Inference methods, such as variational autoencoders [3], can learn powerful generative probabilistic models. To get conceptually simple and highly scalable approaches both the amortized inference and generative model are parameterized as neural networks and trained jointly. Combined with models for sequential data, e.g., state-space models, these techniques form the backbone for many approaches to prediction, control, and model-based RL in robotics (,e.g., [1]). Yet, recent results in related domains indicate that amortized can cause a gap in the quality of the inference distribution. This gap, in turn, results in poor generative models that struggle with estimating uncertainties and often require specific architectural modifications to get adequate performance in downstream tasks.

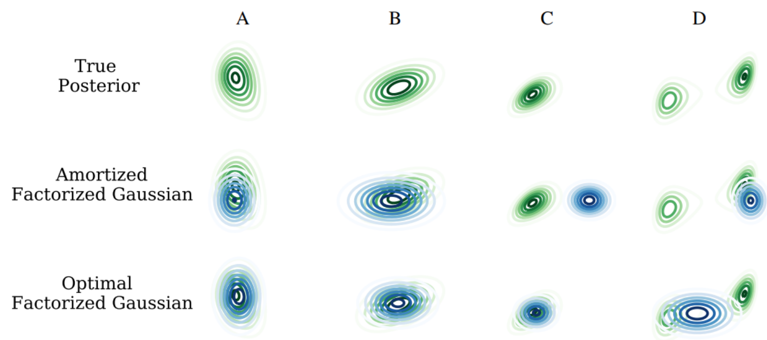

Figure 1: When comparing the amortized inference distributions (second row) with the optimal inference distributions (third row) on a simple example we can already note large differences in quality (Picture taken from [2])

In this thesis, we want to investigate how much state space models suffer from those effects, how this influences performance in downstream tasks, and how we can learn using improved inference approaches.

Tasks

- Getting familiar with recent approaches to general non-amortized and amortized variational inference and how to apply them to state space models.
- Design simple toy tasks to analyze these approaches, investigate the amortization gap, and work on finding scalable ways to reduce it.
- Use these inference methods for simultaneous inference and model learning and evaluate the quality of the learned generative model both directly and in downstream tasks, e.g., control.

References

[1] Philipp Becker and Gerhard Neumann. On uncertainty in deep state space models for model-based reinforcement learning. *Transactions on Machine Learning Research*, 2022.

[2] Chris Cremer, Xuechen Li, and David Duvenaud. Inference suboptimality in variational autoencoders. In *International Conference on Machine Learning*, pages 1078–1086. PMLR, 2018.

[3] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.