Networks for Variations: A Review of Normalizing Flows for Bayesian Variational Inference

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Introduction

In many technical fields, modelling complex systems is in recent years achieved using Deep Learning (DL) instead of setting up domain-suitable inferential statistical models [BAK18; Bre01]. The success of DL can be attributed to the potential for using similar algorithms to achieve high prediction accuracy across different big data problems [Par15]. However, a need for moving these high-accuracy, black box methods towards more robustness and explainability has been highlighted. Seeking this goal, methods have been developed for characterising complete distributions of model predictions, parametrizations or training data instead of only focusing specific realisations of these. This distributional view of DL is used in Deep Generative Modelling (DGM) and in the wider context Bayesian Machine Learning (BML). For both the task of DGM specifically and the general task of approximating posterior distributions in BML, robust and general methods for constructing complex distributions are needed. Normalizing Flows (NF's) specify a scalable mechanism allowing for the representation of arbitrary distributions. This method is here reviewed with a focus on its' relevance for DL.

Fundamental Concepts

State of the Art

Open Problems

References

[BAK18] Danilo Bzdok, Naomi S. Altman, and Martin Krzywinski. "Points of Significance: Statistics versus machine learning". In: *Nature Methods* 15 (2018), pp. 233–234.

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[Par15] Roger Parloff. "Why Deep Learning Is Suddenly Changing Your Life". In: *Fortune* (Sept. 28, 2015). URL: `https://fortune.com/longform/ai-artificial-intelligence-deep-machine-learning/` (visited on 06/10/2022).