

Variational Inference and Deep Generative Models

Wilker Aziz and Philip Schulz

1 Description

NLP has seen a surge in neural network models in recent years. These models provide state-of-the-art performance on many supervised tasks. Unsupervised and semi-supervised learning has only been addressed scarcely, however. Deep Generative Models (DGMs) make it possible to integrate neural networks with probabilistic graphical models. Using DGMs one can easily design latent variable models that account for missing observations and thereby enable unsupervised and semi-supervised learning with neural networks. The method of choice for training these models is variational inference.

This tutorial offers a general introduction to variational inference followed by a thorough and example-driven discussion of how to use variational methods for training DGMs. It provides both the mathematical background necessary for deriving the learning algorithms as well as practical implementation guidelines. Moreover, we discuss common pitfalls that one may encounter when using DGMs for NLP applications (such as the latent variable being ignored by the model) and discuss potential solutions from a theoretical and practical perspective. Importantly, the tutorial will cover models with continuous and discrete variables.

The tutorial starts by motivating the need for approximate inference methods from well-known models such as LDA (Blei et al., 2003) and factorial HMMs (Ghahramani and Jordan, 1996). It then derives the variational objective (evidence lower bound) in detail and relates it expectation maximisation. This is done to provide the audience with a point of reference as we assume the EM algorithm to be known to most participants.

Next, we present the general idea of a DGM and explain why it those models have not been widely used until a couple of years ago. We illustrate the problem with a discussion of the wake-sleep algorithm (Hinton et al., 1995). The next part of the tutorial is dedicated to variational autoencoders (Kingma and Welling, 2014; Rezende et al., 2014). We derive the Gaussian reparametrisation that makes it possible to sample stochastic gradient estimates and thus use backpropagation for training (Kingma and Welling, 2014; Rezende et al., 2014; Titsias and Lázaro-Gredilla, 2014). We then discuss conditions under which this simple training procedure may fail

and offer modifications (e.g. downscaling the KL-term of the variational objective [Bowman et al., 2016](#)).

In the last part of the tutorial, we focus on discrete latent variable models which can generally not be trained using a reparametrisation. Instead they use the score-function gradient technique ([Williams, 1992](#); [Blei et al., 2012](#)). This is yet another way of sampling stochastic gradient, however, the variational objective stays unchanged. Providing the audience with the necessary tools for constructing DGMs with continuous and discrete variable will enable them to conduct research with DGMs without being limited to only a few distributions.

The slides used in the tutorial can be viewed and downloaded from <https://github.com/philschulz/VITutorial>. The slides for discrete latent variables will be added soon.

The tutorial is complemented by a practical coding exercise. The exercise is implemented in a Python notebook and provides the user with a step-by-step walkthrough through the creation of a variational autoencoder. The notebook can be downloaded from https://github.com/philschulz/VITutorial/blob/master/code/vae_notebook.ipynb. While we will not have enough time to do the coding exercise during the tutorial, the audience will be encouraged to do the exercise in their own time and contact us with any questions they may have.

2 Outline

Time	Content
10 mins	Welcome and motivation for approximate inference techniques
20 mins	Derivation of variational inference and relationship to EM
10 mins	Mean field variational inference
10 mins	Introduction to Deep Generative Models
15 mins	Wake-sleep algorithm
10 mins	Variational Autoencoder
20 mins	Gaussian reparametrisation and stochastic gradient sampling
15 mins	Problems with training DGMs
15 mins	Coffee break
20 mins	Semi-supervised learning in DGMs and the need for discrete latent variables
20 mins	Score-function gradient (REINFORCE)
10 mins	Examples of models that use the score-function gradient
5 mins	Wrap-up and goodbye

3 Instructors

1. Wilker Aziz

- Affiliation: University of Amsterdam
- E-mail:
- Website: <http://wilkeraziz.github.io>

2. Philip Schulz

- Affiliation: University of Amsterdam
- E-mail: P.Schulz@uva.nl
- Website: philipschulz.org

4 Estimated Audience Size and Previous Editions

5 Technical Requirements

6 Venues

The preferred venue for this tutorial is ACL 2018. The reason is that we expect an audience with a strong technical background and a keen interest in new machine learning techniques at this conference. EMNLP 2018 would also be possible for the same reasons. However, we reckon that we can reach a larger audience and thus better disseminate these new techniques at ACL. In particular, ACL attracts a more balanced mix of technical and non-technical audiences and thus gives us the chance to relate Deep Generative Models to researchers who may not even be aware of them.

NAACL and Coling are dispreferred options since the former is regional and the latter has a strong focus on linguistic insights. While we do believe that Deep Generative models can enable and enhance new the linguistic investigation of language data, we are not sure that the audience at Coling would feel attracted to a machine-learning-focused tutorial like ours.

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