Advanced machine learning
Suggested topics for student presentations

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1 Student presentation

The goal is to give a 45 minute lecture on a machine learning topic. Here are some suggestions together with initial entries to the literature. You are encouraged to explore the literature to deepen or alter these initial suggestions. You can also propose an entirely different topic, for instance by going deeper into one or more of the articles that are presented during the lectures.

1.1 Replicated Monte Carlo methods

Standard Monte Carlo methods can be generalized to include multiple temperatures and auxiliary variables (clusters). In the presentation, you summarize the original ideas, discuss recent theoretical advances and interesting applications. See [Neal, 1996, Wang and Swendsen, 2005, Barbu and Zhu, 2005] and BRML 27.5.2.

1.2 Gaussian processes

Prepare a lecture on Gaussian processes (for instance BRML ch 19 or Bishop[1] ch 6) and some of their applications (see for instance [Liu et al., 2018]).

1.3 Time series modeling

Prepare a lecture on time series modelling (for instance BRML ch 23 or Bishop ch 13 and some of their applications in bioinformatics, speech recognition, or object tracking (see for instance BRML ch 23.5 for references).

[1] Pattern recognition and machine learning by Christopher Bishop.

1.4 Quantum Boltzmann Machine

The quantum Boltzmann machine is a method to learn a quantum Hamiltonian such that its quantum ground state encodes the statistics of a classical data set. Make a presentation on the quantum Boltzmann Machine based on [Kappen, 2020].

1.5 Dimension reduction methods

Give an overview of methods for dimensional reduction of data. These methods are useful for data visualization and feature extraction. The simplest linear examples are PCA and SVD. Other popular methods are PLSA and non-negative matrix factorisation (see for instance BRML ch 15 and [Lee and Seung, 1999, Lee and Seung, 2001])

1.6 Autoregressive variational inference

This paper proposes a method for approximate inference by approximating the target distribution by a directed graph. Sampling from this directed graph is easy using the idea of ancestral sampling. The parameters of the directed graph are optimized using a variational approach. Here an autoregressive network is used [Wu et al., 2019]

1.7 Model comparison

The Bayesian approach to model comparison requires the estimation of the so-called evidence or Bayes factor $p(D|\mathcal{H}_i)$ with D the data and $\mathcal{H}_i$ the different model hypotheses. The paper [Vyshemirsky and Girolami, 2007] discusses various methods to estimate the evidence based on Monte Carlo sampling. EXTRA: apply one or more of these methods to compute the evidence $p(D|\alpha)$ with α the regularization parameter for the perceptron learning discussed in the MCMC exercise of week 1.

1.8 Sparse regression

Regression with a L_0 or L_1 norm penalty on the parameters yields sparse solutions where a subset of parameters is estimated as zero. In the case of L_1 penalty and ordinary regression the problem is convex and yields the efficient Lasso method [Friedman et al., 2007, Friedman et al., 2010] In the case of L_0 penalty one can obtain superior results but the problem is not convex and can be solved using either Gibbs sampling [George and McCulloch, 1993] or a variational mean field approximation [Kappen and Gómez, 2014].

1.9 Neural data analysis and anaesthesia

This paper [Muñoz et al., 2020] uses the so-called ϵ-machine to model the effect of anaesthesia on brain dynamics in the fruitfly drosophila.

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