Bayesian machine learning

Syllabus

A. Course Description

This course is about constructing statistical learning models based on Bayesian perspective. In this course students will be provided with a theoretical background in bayesian statistics and computational methods with an emphasis on the practical advantages of the bayesian approach. Many probabilistic points of view of standard machine learning models will be explored and implemented in practical sessions. Half of this course is expected to be practical sessions in Python.

B. Course Overview

1. Course Composition

This course is structured in six main sessions :

1. **Introduction to bayesian statistics.** This session aims to introduce bayesian statistics and how to apply bayesian inference on probabilistic models.
2. **Latent variable models and Expectation-Maximization (EM) algorithm.** Define latent variables and how to apply them to simplify probabilistic models. These simplified models can be trained with an EM algorithm. We will see the theoretical foundation of EM algorithms before exposing their limitations.
3. **Variational Inference (VI)**. Aims to introduce one of the most popular deterministic approximation methods and how it can overcome one of the possible limitations of the general form of EM algorithm.
4. **Markov Chain Monte Carlo (MCMC).** A complementary stochastic method of the variational inference will be developed in the fourth session. The students will be provided with a theoretical background on sampling strategies.
5. **Advanced topics** : **Bayesian Neural Network and sequential data**. Be up to date with some recent advances in Bayesian machine learning.
6. **Oral presentation.** Be able to present your work on one of the research articles in bayesian machine learning (programming in Python).

2. Target Skills and Learning Outcomes

The skills that should be acquired while taking this course are summarized in the following table

Skills	**Learning outcomes**
Bayesian statistics	Students will be able to define a probabilistic model and apply bayesian inference

Bayesian Machine Learning with python	Be able to design and implement in python a bayesian machine learning model for classical supervised or unsupervised learning.
Limitations of Bayesian methods	Be able to understand the pros and cons of bayesian methods : when and why should we apply them ?
Recent advances of bayesian machine learning	Bayesian machine learning is a growing domain of a sub-field of machine learning. After this course students will be able to understand the abstract of most research papers on this subject.
Topic modeling	Be able to identify topics in textual data with unsupervised methods.

C. Assessment Model

The evaluation will consist of a group project based on a research article : one article for each group.

- (50%) Each group reports and reimplements in python the research article. Many initiatives like more experimentations or identification of limitations of the paper will be greatly appreciated.
- (50%) during the last lecture, each group will give an oral presentation in front of the class. Their presentation should be understandable by others. The idea is to present a high-level point of view of their respective research paper.

D. References & Resources

- Christopher M. Bishop, “Pattern recognition and machine learning” Springer, 2006
- Sergios Theodoridis, “Machine Learning : a bayesian and optimization perspective” Academic Press, 2020

E. Hardware and Software

Students should have Python and Jupyter Notebook installed. The easiest way would be installing Anaconda directly on your machine.

F. Prerequisites

Students should have taken :

- a course in probability and/or computational statistics
- a course in statistical learning (either a complete supervised or unsupervised learning course)

Students should also have a basic knowledge of the language python (or R).

G. Sessions Contents

1. Session 1 :
    a. Introduction to bayesian statistics
    b. <<Probability, frequentist statistics, bayesian statistics, probabilistic model, bayesian inference, conjugate distribution>>
    c. Case study : Linear regression, Naive Bayes, Normal / Gamma / Beta distribution as prior distribution
2. Session 2 :
    a. Latent variable models
    b. <<Expectation Maximization algorithm, probabilistic clustering : GMM and k-means probabilistic dimensionality reduction : PCA>>
    c. Case study (practical session) : GMM implementation in python
3. Session 3 :
    a. Variational Inference
    b. <<Mean Field approximation, Topic Modeling, Latent Dirichlet Allocation with VI>>
    c. Case study (practical session) : text mining and LDA
4. Session 4 :
    a. Markov Chain Monte Carlo
    b. <<Monte Carlo estimation Markov chain Gibbs Sampling Metropolis-Hastings>>
    c. Case study (practical session) : text mining and LDA

5. Session 5 :
    a. Advanced topics
    b. <<Bayesian Neural Network, Hidden Markov Chain>>
6. Session 6 :
    a. Oral presentation
    b. <<research paper>>

H. Class Policies

- Respectful consideration of one another’s perspectives;
- Do not hesitate asking questions : there’s no dumb questions;
- I’m available by email for questions related to this course