CompSci 299: Individual Study

Topics in Approximate Bayesian Inference, Fall 2017

Instructor: Padhraic Smyth
Supervisor: Eric Nalisnick
Meetings: Tuesdays at 1pm, DBH 4228

Course Summary

The goal of this independent study is an in-depth investigation of cutting-edge methods for approximate Bayesian inference. Ideally, novel work worthy of submission to a reputable academic conference or workshop will be done by the end of the quarter. At minimum, solid understanding of and ability to implement foundational techniques—such as Laplace approximations, mean field (variational Bayes) approximations, and their stochastic versions—will be required for satisfactory performance.

Evaluation

Student evaluation will be done via two written reports. The first is a preliminary draft, due Monday Nov. 6, 2017, that summarizes baseline methods, investigation of novel methods, and all experiments performed. The draft will be graded more for accuracy of content rather than style or polished exposition. Submission of an instructor-approved paper to a NIPS workshop can serve as a satisfactory mid-point draft. The second is a final draft, due Wednesday Dec. 13, 2017, that professionally presents all work done throughout the quarter and includes discussion of background, related work, and experimental details such that a third party could reproduce them. While producing an academic publication is the ideal outcome of the course, there is no penalty for not producing publishable results.

Logistics

Progress will be tracked via a GitHub repository and a Google document. The GitHub repository, located at `https://github.com/enalisnick/Fall2017_Individual_Study`, should host all implementations and code for running experiments. The Google document (which will be shared with you via email) will serve as a shared log: use it to write notes and to summarize meetings.

Academic Integrity

Students are expected to read and be familiar with **UCI's Academic Integrity Policies** and **UCI's definitions and examples of academic misconduct**. Failure to adhere to this policy can result in a student receiving a failing grade in the class. All programmatic implementations and writing must be the student's own work. One exception is for implementation of existing methods for purposes of experimental comparison; existing open source implementations can be used. Writing must contain properly-formatted citations giving appropriate intellectual attribution.

Schedule

1. OCT. 2 - 6: Laplace approximation (LA), Mean-Field Variational Bayes (MFVB)
2. OCT. 9 - 13: LA and MFVB baselines
3. OCT. 16 - 20: Novel method investigation / toy experiments
4. OCT. 23 - 27: Implement novel method
5. OCT. 30 - NOV. 3: Write-up work (description and experiments with baselines and novel method)
6. **NOV. 6: Mid-Point Report Draft Due [20% of grade]** (or submit NIPS workshop paper)
7. NOV. 6 - 10: More investigation / refinement of novel method
8. NOV. 13 - 17: More investigation / refinement of novel method
9. NOV. 20 - 24: More investigation / refinement of novel method
10. NOV. 27 - DEC. 1: More investigation / refinement of novel method
11. DEC. 4 - 8: More investigation / refinement of novel method
12. **DEC. 13: Final Report Due [80% of grade]**
13. FEBRUARY 2018: Submit ICML paper

Reading List

Bayesian Methods, Model Selection, and Occam's Razor

1. *Bayesian Methods for Machine Learning*, by Radford Neal
2. *Bayesian Interpolation*, by David MacKay
3. *Information Theory, Inference, and Learning Algorithms*, Chapter 28
4. *A Note on the Evidence and Bayesian Occam's Razor*, by I. Murray and Z. Ghahramani
5. *Occam's Razor*, by C. Rasmussen and Z. Ghahramani
6. *Bayesian Model Averaging is Not Model Combination*, by Tom Minka

Overviews of Variational Inference

1. David Blei's Course Notes
2. Variational Inference: A Review for Statisticians
3. David Blei's NIPS Tutorial Slides [video]
4. *Variational Bayesian Theory*, by Matthew Beal

5. David MacKay's Lecture: *Approximating Probability Distributions*

Laplace Approximation

1. *Information Theory, Inference, and Learning Algorithms*, Chapter 27
2. Jose Miguel Hernandez-Lobato's Slides

Variational Bayes

1. *Variational Bayesian Methods*, Wikipedia
2. *Information Theory, Inference, and Learning Algorithms*, Chapter 33
3. *Stochastic Variational Inference*, by M. Hoffman, D. Blei, C. Wang, and J. Paisley
4. *Hierarchical Variational Models*, by R. Ranganath, D. Tran, and D. Blei

Variational Inference for Non-Conjugate Models

1. *Variational Inference in Nonconjugate Models*, by C. Wang and D. Blei
2. *Nonparametric Variational Inference*, by S. Gershman, M. Hoffman, and D. Blei
3. *Variational Bayesian Inference with Stochastic Search*, by J. Paisley, D. Blei, and M. Jordan
4. *Fixed-Form Variational Posterior Approximation through Stochastic Linear Regression*, by T. Salimans and D. Knowles
5. *Efficient Gradient-Based Inference through Transformations between Bayes Nets and Neural Nets*, by D. Kingma and M. Welling

Interesting Papers, Miscellaneous

1. *Stein Variational Gradient Descent*, by Q. Liu and D. Wang
2. *Black-Box Alpha-Divergence Minimization*, by J. Lobato, Y. Li, M. Rowland, D. Lobato, T. Bui, and R. Turner
3. *Renyi Divergence Variational Inference*, by Y. Li and R. Turner
4. *A Divergence Bound for Hybrids of MCMC and Variational Inference*, by J. Domke
5. *Variational Boosting*, by A. Miller, N. Foti, and R. Adams
6. *Deep and Hierarchical Implicit Models*, by D. Tran, R. Ranganath, and D. Blei
7. *MAD-Bayes: MAP-based Asymptotic Derivations from Bayes*, by T. Broderick, B. Kulis, and M. Jordan